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Smart Pricing for Smart Grid

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Smart Pricing for Smart Grid

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Contents

Abstract

Flat-rate electricity tariffs in Great Britain, which have no price variation throughout a day or a year, have been ongoing for decades to recover the cost of energy production and delivery. However, this type of electricity tariff has little incentives to encourage customers to modify their demands to suit the condition of the power supply system. Hence, it is challenged in the new smart grid environment, where demand side responses have important roles to play to encourage conventional energy efficiency and support the integration of renewable generation. In order to accommodate this new environment, the investigations of smart tariff designs and their applications in demand side response are therefore carried out from three main aspects.

In a high carbon system dominated by controllable fossil generation where energy peaks typically coincide with those of networks, smart tariffs are developed by statistically tracking dynamic energy price variation tendencies and categorising real-time prices to form time-of-use patterns that capture the most significant price variations without compromising too much accuracy in total energy revenue from customers.

In a low carbon system where energy peaks and network peaks may not be in synchronism at all times, additional complications will be raised when developing smart tariffs and optimal demand side response strategies. A new concept is developed in this thesis to allow shared utilization of energy storage between customers and distributed network operators to respond to conflicting energy price and network conditions. In this work, two operation models of storage share are implemented. One is fixed share between customers and network operators regardless of network conditions, and the other is dynamic share that storage capacity utilized by network operator changes with network condition. The consequential system benefit in terms of energy cost reduction and network cost saving is evaluated and converted into per unit cost reduction in the energy bill.

Addition to technical solution in the form of storage, the benefit from household demand shifting, such as shifting wet appliances, in the presence of smart tariffs is evaluated. The value of household demand shifting is quantified as an equivalent storage capacity for the investigation of complementarity between technical and social interventions.

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List of Abbreviations

Alternating Current	AC
Carbon Dioxide	CO_2
Critical-Peak Pricing	CPP
Direct Current	DC
Department of Energy & Climate Change	DECC
Distributed Generation	DG
Distribution Network Operators	DNOs
Demand Side Response	DSR
Energy Management System	EMS
Great Britain	GB
Great British Pound	GBP
High Voltage	HV
Light-Emitting Diode	LED
Long-Run Incremental Cost	LRIC
Low Voltage	LV
Marks and Spencer	M&S
Office of Gas and Electricity Markets	Ofgem
Pumped Hydroelectric Energy Storage	PHES
Photovoltaic	PV
Real-Time Pricing	RTP
Southern Electric	SE
State of Charge	SoC
Time-Of-Use	TOU
United Kingdom	UK
United Nations	UN

Chapter 1

Introduction

THIS chapter briefly describes the background, motivation, challenges, objectives, and contributions of this work. It also provides an overview of the thesis.

1.1 New Environment for Electricity Development

1.1.1 Carbon Emission Reduction

Global carbon dioxide (CO_2) emission has undergone significant rise due to the dramatic increment of fossil fuel consumption over the past decade. As shown in Figure 1-1, the carbon emission in 2010 is nearly three times as much as that of 1965. This rapid growth in CO_2 emission is a major concern for global climate, as it retards earth cooling and increases average global temperature, which would consequently drive sea level to rise. At present, all countries are confronting the problem and seeking ways to reduce greenhouse gas emissions. In order to fight global warming, over 180 nations committed themselves to the United Nations (UN)'s Kyoto Protocol, a global agreement that places binding limits on national CO_2 emission levels for different countries [1].

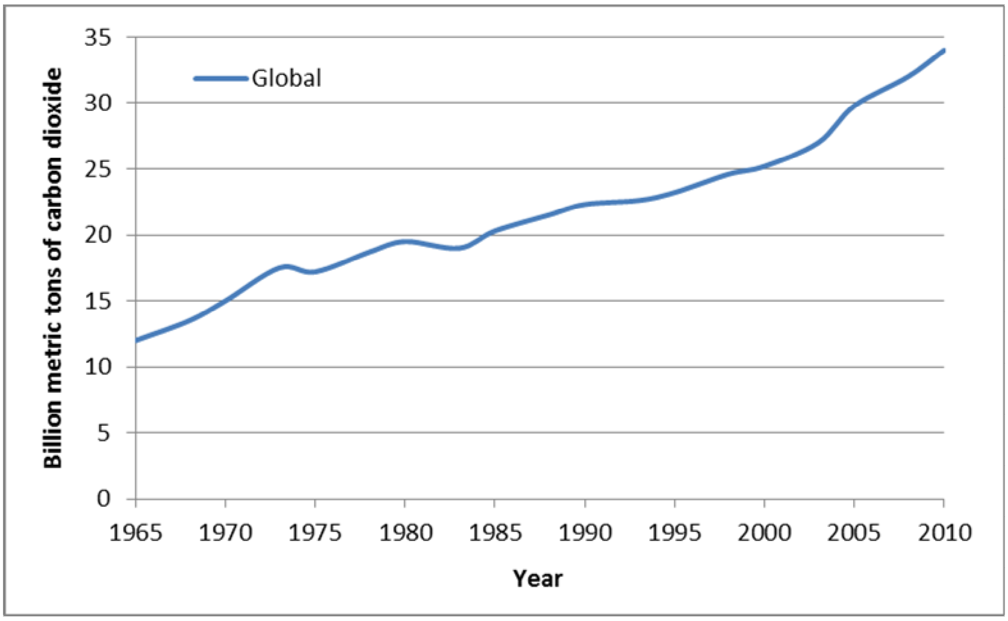


Figure 1-1 Global carbon dioxide emissions [2]

In the United Kingdom (UK), the Climate Change Act 2008 sets binding targets of 80% cut in greenhouse gas emissions by 2050 against 1990 baseline. In order to set a clear pathway towards this ambitious target, a system of carbon budgets is introduced, specifying binding limits on the permitted emissions in successive five-year periods beginning from 2008. These four carbon budgets presented in Table 1-1 were set in June 2011, clearly defining carbon budget levels and the percentages of reductions.

The carbon budget level is set at 2782mt in 2017, which has a reduction of 29% compared to the 1990 level. Then, it is expected to continue dropping to 1950mt in the following decade.

Table 1-1 The Climate Change Act 2008 and the carbon budget framework [3]

	First carbon budget (2008–12)	Second carbon budget (2013–17)	Third carbon budget (2018–22)	Fourth carbon budget (2023–27)
Carbon budget level (million tonnes carbon dioxide equivalent ($mtCO_2$))	3,018	2,782	2,544	1,950
Percentage reduction below base year levels	23%	29%	35%	50%

1.1.2 Renewable Generation

Among all the contributors to CO_2 emissions in the UK, electricity is the largest sector, accounting for 38% of the total [4]. Driven by the green policies proposed by the UK government, renewable generation technologies are encouraged to be integrated into power systems in order to reduce carbon emissions and striding towards a sustainable low carbon development.

Over recent years, a number of renewable energy technologies have been utilised to generate clean energy in the UK. Solar energy, wind power, bioenergy and others have contributed significantly to electricity generation, in addition to conventional hydroelectricity generation. By 2013, the share of renewable electricity generation has increased to 13.7% with a generation capacity of 19.1 GW [5].

Among the key renewable generation technologies, the UK government emphasises the development of solar photovoltaic (PV) particularly because of its versatility and scalability [6-8]. By the end of 2013, the installation cost of solar panel had fallen to around half of that in 2010, and the average domestic solar PV system was 3.5kWp with a cost between £5250 and £6470 [9]. Besides, solar PV panels have been installed for nearly half million households together with thousands of business premises. The PV capacity is 2.5 GW at present, accounting for 13% of national renewable installed capacity [5]. The Department of Energy & Climate Change (DECC) forecasted that PV capacity is to reach 10GW by 2020 [6].

When high density renewable generation is connected to power grid, problems in terms of thermal, voltage, and stability constraints may arise as a result of its intermittency. These pressures can be mitigated by conventional network expansion/upgrading which is expensive and time-consuming. Demand side response (DSR) can relieve network congestion as a cheaper solution by aligning demand with available renewable energy.

1.1.3 Demand Side Response

Demand side response (DSR) is defined as a program that encourages demand reduction and load shifting by end customers to avoid periods with expensive generation or network congestion [10]. The DSR in this thesis mainly refers to load shifting.

Over the past years, the role of DSR has been highlighted due to its remarkable impacts on economic benefit and carbon emission. As shown in Table 1-2, DSR can lead to financial benefits by facilitating wholesale cost savings and deferring network investment. If 10% of the peak demand in the UK is shifted to off-peak hours, the maximum daily benefit from energy cost reduction can be £1.7m. Meanwhile, annual network investment cost saving is quantified as £28m. In addition, the load shifting can lead to a CO_2 emission reduction up to 2,550t. Therefore, DSR is expected to be of significant importance for electricity generation and system operation.

Table 1-2 Quantified benefits from load shifting [10]

	Shift 10% peak load
Daily wholesale energy cost savings (£)	0.7m to 1.7m
Annual network investment savings (£)	28m
Daily carbon emission savings (tCO2)	800 to 2,550

The flexibility in electricity consumption is commonly used to realize DSR. Conventionally, the flexibility refers to the load shifting through the changes in customers' behaviours. However, this type of social intervention may have limited effects as a large amount of electricity use is inflexible. An alternative approach to facilitate active DSR is a technical solution, in which local energy storage is employed for peak shaving and valley filling.

1.1.4 Energy Storage

Energy storage units can store energy during off-peak hours and release it during peak hours. Due to the capability of shifting energy usage in terms of time, energy storage devices are able to improve the flexibility of energy consumption. When DSR is enabled by energy storage, DSRs can be achieved with minimal change of energy consumption.

In 2050 pathways report issued by DECC [11], energy storage solution from demand side contributes to all the pathways to reduce carbon emission, meet demand, and secure energy system [12]. Meanwhile, over five million Great British Pound (GBP) have been spent by UK government for the innovation in energy storage technologies [13].

Even though electricity is very expensive to be stored in significant quantities, it can often be stored more cheaply for a few hours or days on a decentralized basis [14]. Several advanced technologies are undergoing development, including battery storage, flywheels, pumped hydroelectricity storage, geological storage, and supercapacitors [15]. Among these energy technologies, lithium-ion batteries cost £650 per kilowatt hour, flow batteries cost £1,500 per kilowatt hour, high-temperature batteries cost £1850 per kilowatt hour, and flywheels cost £750 per kilowatt hour [16]. As the costs of lithium-ion batteries are the cheapest, they can be utilised for domestic customers to facilitate DSR.

1.1.5 Electricity Pricing

If DSR is enabled by energy storage, a key implementation approach is to use electricity in reaction to pricing signals. Generally, the pricing signals are made up of a number of elements, including energy cost in wholesale market, transmission and distribution cost in networks, environmental cost in environment protection, and so forth.

An example of the electricity price in Great Britain (GB) is selected to show its present composition. The breakdown of electricity price for end customers in 2013 [17] is illustrated in Figure 1-2, where the volume of each part is shown. These percentages are obtained by averaging annual costs across all the incumbent suppliers and payment methods across GB. As seen, energy cost makes up over half of the electricity cost and the proportion of distribution charges reaches nearly 20%. These two components account for more than 70% of the total cost.

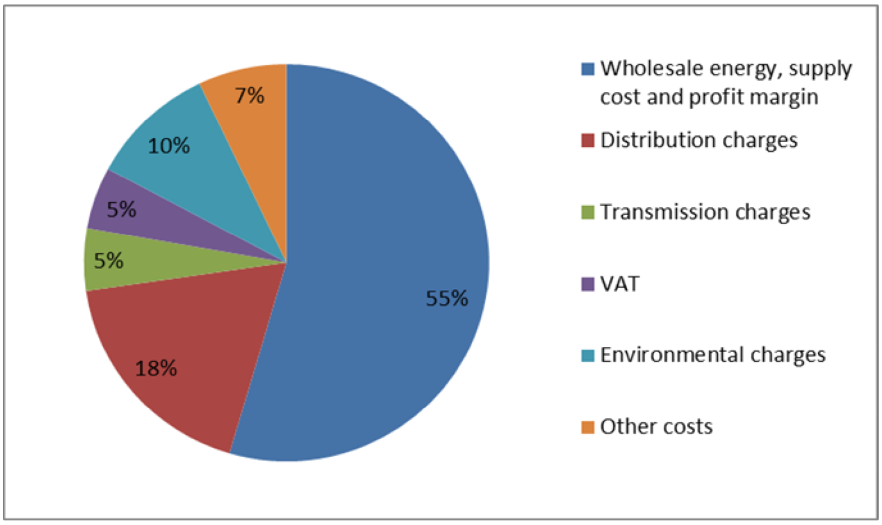


Figure 1-2 Breakdown for electricity price

Based on the constitution of electricity price given above, the factors of wholesale energy cost and distribution cost need to be considered chiefly in electricity pricing development.

1.2 Research Motivation

In GB, the increase of domestic electricity use has been a major factor for the peak demand growth [18]. However, a majority of consumers purchase their electricity at flat unit rates, regardless of time-of-day or day-of-year, offering little incentives for mass consumers to reduce national peaks. When renewable generation and DSR enabled by energy storage are implemented in smart grid environment [19, 20], the conventional flat-rate tariff mechanisms are challenged in the new environment especially from the following limitations.

i) to track energy cost: the energy price in wholesale market is time-varying, but the retail price in a flat-rate tariff does not vary with the time of usage. Therefore, conventional tariffs with fixed rates are not closely linked to energy generation costs.

ii) to trigger DSR: flat-rate tariffs have little incentives to enable customers to shift load away from peak periods. Consequently, DSR under flat-rate tariffs cannot be guided to improve energy supply security or reducing investment cost.

iii) to deliver benefits to customers: The failure of reflecting the benefits from DSR is unfair for customers who eventually pay for electricity usage. At the same time, the conventional flat-rate tariffs have no incentives to encourage customers to participate in DSR and energy management.

In order to overcome the issues under conventional flat-rate tariffs, smart tariffs, which are new forms of retail tariffs are proposed to encourage responses facilitated by in-home energy storage for distributed energy management [21]. In order to improve the effectiveness of the responses, this thesis for the first time proposes the method of utilizing storage by not only customers but also distribution network operators (DNOs). It aims at maximising the benefits from the deployment of in-home energy storage and energy management system to optimise energy cost and network efficiency for the interest of end consumers. In this thesis, smart pricing refers to the design of smart tariffs, and the smart tariffs refer in particular to

i) Smart variable tariffs designed to provide consumers or energy management system with time-varying prices: In order to shift load from peak to off-peak periods by clipping peak demands and filling them in valleys, variable tariffs, such as time-of-use (TOU) tariffs or real-time pricing (RTP) tariffs, are developed for customers or storage devices to respond to.

ii) Smart fixed tariffs designed to present customers with information on financial saving from their installation of PV panels and deployment of in-home energy storage with integrated energy management system. The economic benefits from renewable energy usage and demand shifting throughout a year are converted into per unit cost reduction for customers.

The application of smart tariffs in this thesis is focused on the domestic sector, where the responses to the proposed tariffs are mobilised through the deployment of in-home energy storage with integrated energy management system. The effects of DSR are examined for homes with and without local renewable generations, which is in the form of distributed PV panels installed on house roofs [22, 23].

1.3 Research Challenges

In the investigations of smart tariff designs and applications in the domestic sector, various challenges are faced:

- **Capturing energy price variation statistically for smart variable tariff design in high carbon systems**

In the GB wholesale electricity market, energy price changes as often as half-hourly and a settlement day is divided into 48 settlement periods accordingly. However, a direct reflection of these half-hourly varying prices to end-users is considered to be too dynamic to be responded. Therefore, the first challenge in smart tariff design is to transfer dynamic prices into tariffs with less price variations statistically.

- **Responding to network and energy pressures simultaneously in low carbon systems**

The dynamic prices in wholesale market can be reflected in smart variable tariffs to encourage customers to respond to them. However, this method is constrained in low carbon systems because energy pressure and network pressure can be conflicting. If the response conducted by storage is only triggered by smart variable tariffs to take advantage of low energy price, it might further increase system congestion and accelerate network reinforcement. Therefore, the challenge in this area lies in the development of the solution to respond to energy and network pressures simultaneously for both energy cost reduction and network investment deferral in low carbon systems.

- **Enhancing energy management to take advantage of distributed generation**

Renewable generation in distribution network is significant for energy management in low carbon system. It may lead to the changes of energy and network pressures due to its capabilities of supplying local demand and enabling storage devices to store energy for peak shaving. Therefore, the biggest challenge here lies in how to mitigate energy and network pressures in the presence of significant renewable generation. Meanwhile, for customers adopting the home area energy storage, PV and energy management, it is important that they can understand the benefits very clearly and easily. Therefore, a simple yet effective benefit delivery method has to be developed to pass the financial gains from efficient usage of distributed generation (DG) and DSR to end users.

- **Assessing the effect of DSR facilitated by flexible demand shifting and energy storage**

A number of previous studies have been conducted to examine the effectiveness of the response from either storage or flexible load at household level [22, 24-26]. However, the benefits from these two measures have never been linked before. Therefore, the values of the responses from technical solution enabled by energy storage and from social solution mobilised by manually shifting flexible load need to be quantified.

1.4 Research Objectives

The major objective of this work is to design smart tariffs and develop corresponding response strategies mobilised by energy storage to explore the benefits in terms of energy cost saving and network cost saving. This work attempts to be carried out to achieve the following targets:

- To develop smart variable tariffs to trigger DSR in high carbon systems;
- To facilitate effective DSR triggered by energy price and network condition in low carbon systems;
- To enhance energy management strategy in the presence of significant renewable generation and to develop smart fixed tariffs to capture consequential financial benefits;

- To evaluate the benefit from household demand shifting in the presence of smart tariffs.

1.5 Contributions

The main contributions of this work are as follows:

- Converting dynamic prices to TOU forms that capture the most significant prices without compromising too much accuracy in total energy revenue from customers;

- Propose optimal battery share between customers and DNOs for energy storage utilization, taking advantage of lower energy prices and mitigating network constraints;

- Propose a new method, defined as “charging envelope”, to enable battery share between customers and DNOs when renewable generation is integrated into distribution system;

- Extend active responses enabled by energy storage to those driven by household demand shifting.

In doing so, this study attempts to:

- Develop RTP tariffs firstly to track energy price variations. Equal interval grouping and hierarchical clustering techniques are then adopted to convert RTPs to TOUs;

- Implement two operation models to utilize shared energy storage. One is fixed share between customers and DNOs regardless of network conditions, and the other is dynamic share that DNO ownership of storage changes with network conditions;

- Encourage customers to respond to smart variable tariffs and enable DNOs to communicate with batteries through the proposed charging envelopes. With the cooperation between charging envelopes and smart variable tariffs, the consequential benefits in terms of energy cost reduction and network cost saving are evaluated over a year and subsequently converted into per unit cost reduction in energy bill;

- Quantify the value of household demand shifting as an equivalent storage capacity for the investigation of complementarity between technical and social interventions.

1.6 Thesis Layout

The rest of the thesis is organised as follows:

Chapter two provides a comprehensive literature review of the current electricity tariffs exercised by major suppliers in GB and worldwide. The pros and cons of them are extensively compared. Besides the assessment of the current tariffs, the requirements of further electricity tariffs are also discussed to support suppliers to take initiatives in tariff innovations.

Chapter three proposes RTP and TOU tariffs to reflect wholesale energy cost variations. The TOU tariffs are innovatively developed by translating the obtained RTP tariffs with two methods, i.e. equal interval grouping and hierarchical clustering methods. The load shifting in response to these cost-reflective smart variable tariffs will lead to wholesale cost saving and peak demand reduction in high carbon systems.

Chapter four proposes a novel approach to facilitate DSR with RTP tariffs and shared storage. The energy storage is operated by customers and network operators together in response to energy price variations and network conditions when these two factors are not conforming to each other in low carbon systems. The impacts of the fixed and the dynamic shared storages on energy costs and network costs are quantified in terms of wholesale energy cost saving and network investment deferral. The proposed approach is then tested on two practical distribution systems to demonstrate its effectiveness and applicability to actual systems.

Chapter five enhances the method of using shared energy storage to respond to energy pressure and network pressure. The novel concept of “charging envelope” is employed to enables solar PV generation to connect to LV distribution networks more efficiently through using in-home storage and smart variable tariffs when the PV penetration level reaches 100%. With the adoptions of distributed energy storage and PV, the whole-system financial benefits are analysed over a year. For benefit transparency, they are converted into per unit cost reduction in energy bill. The effectiveness of the proposed methodology is demonstrated on a practical LV network with substantial in-home DG and storage.

Chapter six extends the active DSR from storage solution to social side by shifting household demand. It is mobilized by shifting wet appliances and the associated benefits in the presence of smart variable tariffs are compared with those from energy storage operation. The cooperation between energy storage and household demand shifting is also investigated for benefit improvement. Lastly, a demonstration is conducted on the distribution system used in the foregoing chapters.

Chapter seven summarizes the key findings from the research and the major contributions of the work.

Chapter eight provides some potential research topics in future work.

Chapter 2

Review of Electricity Tariffs

THIS chapter summarizes a range of electricity tariffs exercised by major suppliers in GB. The smart tariffs explored by other countries are also reviewed for further pricing scheme improvement in the GB electricity market.

2.1 Introduction

Household flat-rate electricity tariffs have been ongoing for decades in GB. The fitness of this type of tariffs is challenged in the new smart grid and smart metering environment, where DSR and renewable generation are expected to play important roles to save energy cost, support network and combat climate change. Generally speaking, most advanced electricity tariffs to date aim to increase supply efficiency and/or reduce supply costs, thus increasing customer numbers in an open electricity market through highly competitive energy price. This chapter reviews a range of electricity tariffs exercised by major suppliers in GB and their associated drawbacks. The need for further development in electricity tariffs is analysed to introduce various tariffs for different types of customers to maximize their participations and thus to reduce energy bills in the future.

2.2 Tariff development in GB

Driven by the target of 15% total energy consumption from renewables by 2020 [27], significant number of distributed generators are to be integrated into the existing network to substitute part of fossil fuel generation. Meanwhile, the demand for electricity continues to rise at around 1% per annum. The conventional approach to accommodate the increasing generation and demand is network reinforcement, which is expensive and time consuming. In order to reduce network investment cost and protect the interests of consumers, DSRs are encouraged to assist secure and sustainable energy supplies.

A critical element in mobilising DSR is economic incentive, which is generally in the form of electricity tariffs and energy products. In GB, flat-rate tariffs are the most common tariffs for small energy users (below 100kW), providing no incentives for individuals to participate in DSR. Although energy prices and congestions costs change over time, the pricing information is only passed on to larger consumers, posing major hurdle for mass consumers to participate in the market and take an active role in DSR. Therefore, in the new environment with significant low carbon generation, the designs of innovative electricity tariffs should follow the following guidelines [28]:

- Consider economic efficiency, costing resources in terms of fuel, conversion costs, and effects on the environment;

- Reflect the costs of generation, transmission and distribution;

- Maintain equity between diverse consumers;

- Ensure simple and transparent tariffs to customers.

There is a significant challenge to move tariffs from flat-rate form to cost-reflective pattern in order to ensure that consumer responses will lead to a positive impact on the supply system. Although cost-reflectivity is a key objective in electricity pricing, new tariffs should not come at high complexity and lack of transparency which could lose consumers' confidence. A further challenge is that there is yet pricing structure to reflect the cost of transferring energy through the LV distribution network where the low carbon technologies will have the largest impact. Therefore, current electricity tariffs require major innovations to reflect both the energy cost variation and the network cost for transfer energy through the LV distribution system.

In the following sections, current electricity tariffs offered by major suppliers in GB are reviewed firstly. The features of these tariffs together with their associated energy products are assessed. The review of different smart tariffs, which were designed in other countries, is also carried out in order to develop innovative tariffs for a future low carbon retail market with significant consumer choices.

2.3 Current Electricity Prices Tariffs Review

Conventional flat-rate household tariffs were developed in 1960s [29]. They reflect the total cost of energy generation, transmission, distribution and supply. At present, neither time-of-day nor time-of-year tariffs has been widely used in GB, the vast majority of consumers purchase their electricity from suppliers at flat-rate tariffs, with no price variations throughout the day and throughout the year.

So far, two types of flat-rate tariffs are provided to domestic consumers: standing charge tariffs and two-tire tariffs. They are described in detail as follows.

- **Standing-Charge Tariffs**

A standing charge is a fixed amount of cost paid annually to electricity suppliers. The costs of meter reading, maintenance, network connection, and so forth are all included in it. Then, the actual consumption is charged at a fixed unit price. The annual standing charge is averaged at £54.35 across the GB's 6 suppliers [30].

- **Two-Tier Tariffs**

Consumers under this tariff are subject to two tier unit prices, where the fixed cost is thus built into the unit rate instead of a stand-alone charge. Tier 1 unit price is applied to the first block of consumers' energy use, recovering the suppliers' fixed cost. Tier 2 unit price is applied to electricity usage at and above the first tier of consumption, recovering suppliers' total operational costs. Generally speaking, Tier 1 unit price is higher than that of Tier 2, and average Tier 1 and Tier 2 unit charges are 17.06p and 12.46p respectively [31]. For households with average consumptions, the first threshold accounts for 768 kWh [31]. Between the two types of tariffs, Two-tier tariffs account for 65 percent of the total population.

In addition to flat-rate tariffs, all suppliers offer Economy 7 [32] or Economy 10 [33] tariffs which have significantly less customer volume of around 9.7% in GB. These tariffs introduce cheaper night or afternoon rate in order to shift load from peak to trough time, thus reducing energy consumption during peak period. The "7" or "10" in the definition means seven or ten hours of lower rate electricity and the time interval of the economic rate may slightly differ from one supplier to another. Economy 7 and Economy 10, representing the simplest products of variable tariffs, attracted residential consumers who have electrical storage heaters to use cheap energy overnight.

2.4 Current Energy Products Review

Nowadays, in addition to the standing charge tariffs and the two-tire tariffs, a range of energy products based on flat-rate tariffs are supplied by large energy companies in retail market to domestic consumers. This section discusses how these tariffs provided by different suppliers benefit consumers and what consumers are encouraged to do so that their energy saving plan could have a noticeable effect. The portfolio of energy products from three electricity suppliers will be described in the following paragraphs.

- **Southern Electric**

A number of energy products are introduced by Southern Electric (SE), such as ”**Batter Plan**” [34], **Go Direct** [35], **Fix Priced Product** [36] and so forth. Among these products, incentive scheme is boosting its market share by helping its clients to reduce their energy bills. Customers who sign up online will be rewarded vouchers from supermarkets. Moreover, monthly direct payment debit will bring a discount on the bill.

- **E.ON**

At least ten energy products supplied by E.ON are available as options for consumers. Namely, they are **Standard Tariff**, **Fixed Price** [37]**, Go Green** [38], **Energy Saver Capped Product** [39], **Standard Tariff, Energy Discount 5, Fix Online** [40], **Energy Saver Capped Product, Track and Save** [41], **Warmassist.** These products are classified by the percentages of discounts on standard prices and the durations of electricity contracts. Besides, these energy products are also associated with benefits from shopping in supermarkets. Due to the diversity of the tariffs in E.ON, it will be easier for customers to find the tariffs suit them best.

- **British Gas**

In British Gas, the products of **Standard Tariff**, **Websaver 4 and 5** [42], **Online Saver** give discounts to customers who would like to sign for long-term contracts. The approaches of getting the best deal from British Gas are managing account online and paying the bill via direct debit. Selecting a dual tariff including both electricity and gas will be more economic for household consumers.

Generally speaking, similarities between the tariffs which are provided by all the suppliers mentioned above are rather obvious. In the first place, nearly all the online account managements are accompanied with efficient ways of electricity bill payments. In the following, most suppliers have their cooperative partners to realise the cooperation between strong companies. The association between strong enterprises is capable of taking advantage of each other's strengths. The premium of helping E.ON users to collect Tesco clubcard point will attract more consumers because their household expenditures will be reduced on both energy and basic living goods. At the same time, these two enterprises will be competitive enough to induce business in their industries. Similarly, SE is associated with Argos and M&S in its long-term energy bills contracts. By and large, a long-term contact will cause a bigger discount together with less termination fee. In addition, some expensive tariffs, such as **Future Tariff** and **Zero Carbon Tariff** which are mainly designed to reduce carbon emission, focus on the application of renewable energy. These tariffs are being accepted by an increasing number of customers gradually and they are expected to be more popular in the next decade. Last but not least, a number of energy products are related to raising funds for charity as well.

Up to now, a lot of British Gas Tariffs, such as **Online Saver, Track and Save, Standard Tariff, Zero Carbon Tariff** and **Future Energy Tariff,** are available under a smart scheme where the information of the tariffs could often be displayed by smart monitors, but the **Web Saver** tariff which provides an additional discount over the standard tariff is not applicative so far.

To sum up the above arguments, the main purpose of the most existing flat-rate tariffs is to attract a number of customers. They are not designed to dynamically follow energy market or reduce network peaks. Therefore, tariff structure optimization is expected to stimulate demand response to support the supply system.

2.5 Smart Tariff Types across the World

Electricity tariffs should play a significant role in stimulating DSR. However, the present tariff structure is not effective in following expensive or intermittent generation or shaving peaks. There are a number of advanced tariffs that are better placed to adjust load.

2.5.1 Time-of-Use

This approach provides a number of pre-defined peak periods with an intention to reduce peak demand thus peak energy prices. Figure 2-1 shows a price profile under a TOU schedule where a day is separated into several peak and off-peak hours and the prices for different periods could vary dramatically [43, 44]. At present, it is the most commonly implemented tariff in smart pricing scheme and the time based rate has been applied by a large number of domestic customers in the US and Canada. Among the present TOU tariffs, some just have simple day and night splits, like Economy 7 mentioned before. However, some have flexible on-peak and off-peak periods which could vary with the change of the date and the season. Generally, TOU tariffs are accompanied with metering smart readings. The settlement under a TOU tariff depends on the electricity consumption in each hour multiplied by the price for that hour.

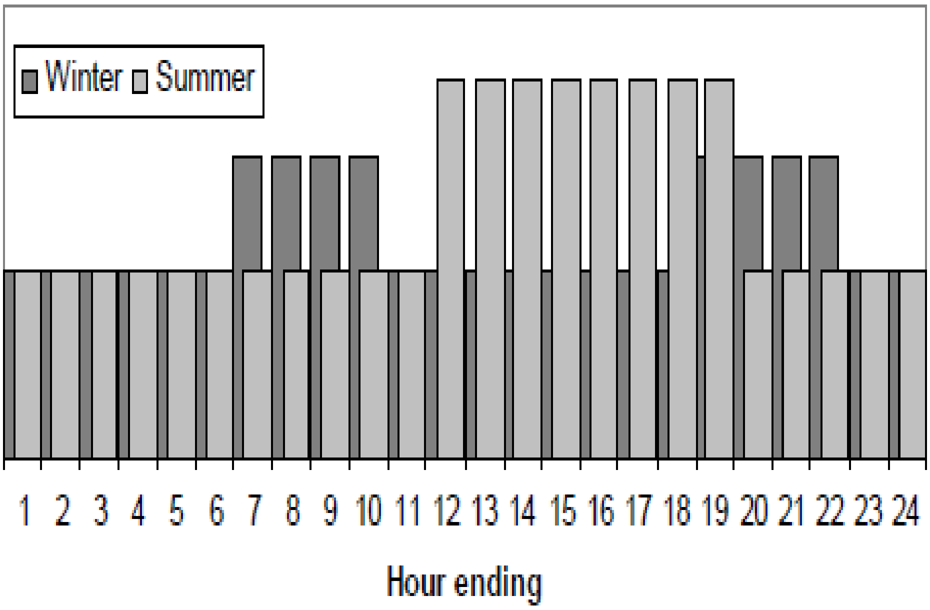


Figure 2-1 An example of summer and winter TOU schedule [45]

2.5.2 Critical Peak Pricing

The peak and off-peak time periods for TOU are pre-defined and fixed for a long time, which can be a season. Critical peak pricing (CPP) is an improved TOU tariff [46] that traces critical supply periods dynamically. The critical peak periods which are always associated with extremely high unit prices can change from one day to another, and the periods are notified to consumers at least one day ahead. To illustrate the tariff structure comparison between TOU and CPP clearly, an example of CPP tariff is provided in Figure 2-2. The highest price in the CPP tariff can last up to 4 to 6 hours within a day [47]. Until now, CPP is still tested by pricing pilots before its implementation on a large scale.

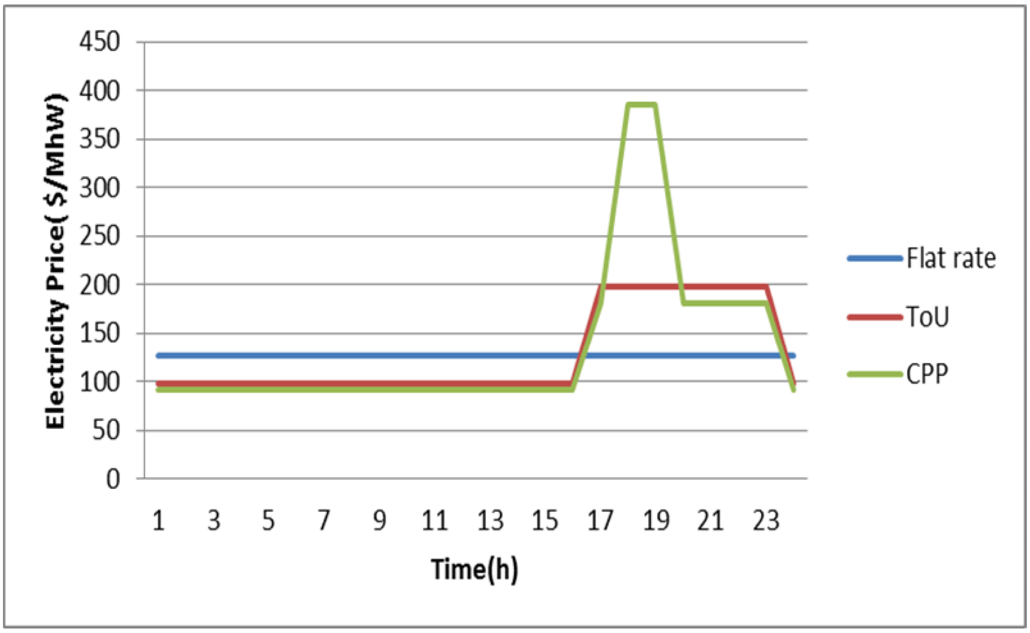


Figure 2-2 An example of CPP tariff structure [48]

2.5.3 Real Time Pricing

RTP provides the most direct way to reflect the dynamics of the GB wholesale price variations throughout a day or throughout a year [49, 50]. The prices of this tariff generally vary every hour or every half-hour. Some suppliers outside GB, such as Illinois Power Company, manage household energy consumption by hourly prices as shown by Figure 2-3. Customers can adjust their electricity usages in response to the RTP tariff which closely links with system conditions, but the demand shifting requires frequent attention to the price variation. So far, RTP is mostly applied in the sector of commercial and industry.

2.5.4 Load Control

With load control tariffs [52], a lower unit price will be provided to customers in exchange for the control of the amount of electricity used for some appliances from time to time.

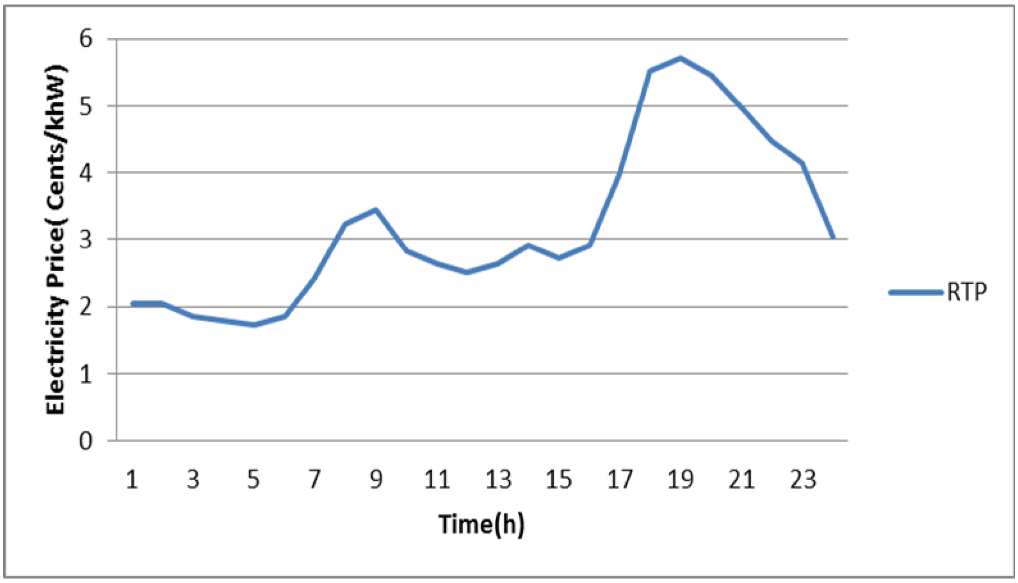


Figure 2-3 The real-time prices of Illinois Power Company on 15 December 2009 [51]

2.5.5 Maximum Demand

The tariff, which is used in France and Italy [53], charges consumers according the agreed peak demand between suppliers and consumers.

2.6 Assessment of TOU and CPP

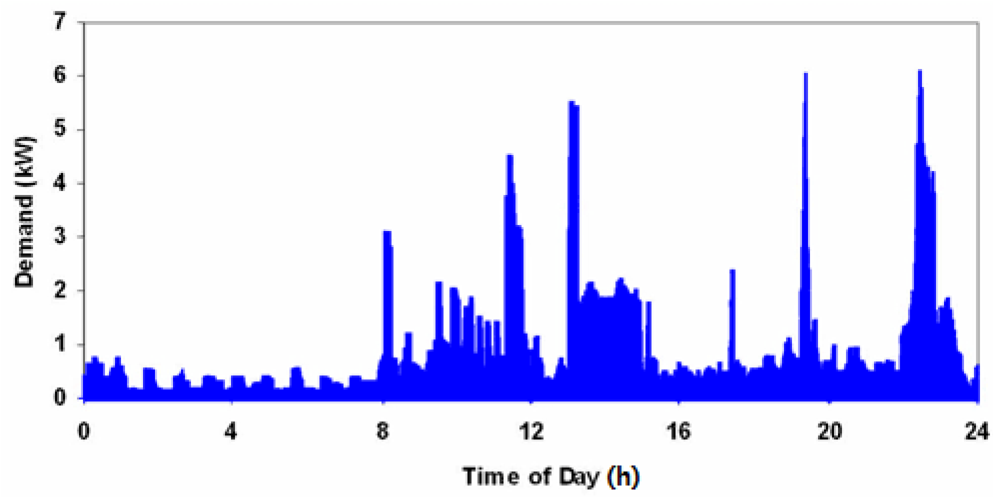
As described in the Section 2.5, the tariffs of TOU and CPP are typically designed with a minimum two or three peak time periods, and the determinations of the time windows largely depend on the generation capacity and real-time demands. Broadly speaking, TOU is suitable for the circumstance that the amount of demand and generation could be predicted beforehand and then it attracts customers by cost-reflective prices to encourage customers to participate in DSR. The tariff of CPP focuses more on the uncertainties of critical peak price rate and its duration. To be specific, it emphasizes the critically important hours of a year by introducing an extremely high rate so that the demand is attempted to be limited within the range of generation or network capacity. Therefore, both TOU and CPP tariffs are linked closely to wholesale market price and are effective on peak shaving and valley filling in energy consumption managements.

The initial aim of smart tariff development and DSR improvement is to realise efficient generation together with electricity bill reductions for end-users. However, the adverse effects of inefficient demand responses are also exposed in the processes of their implementation.

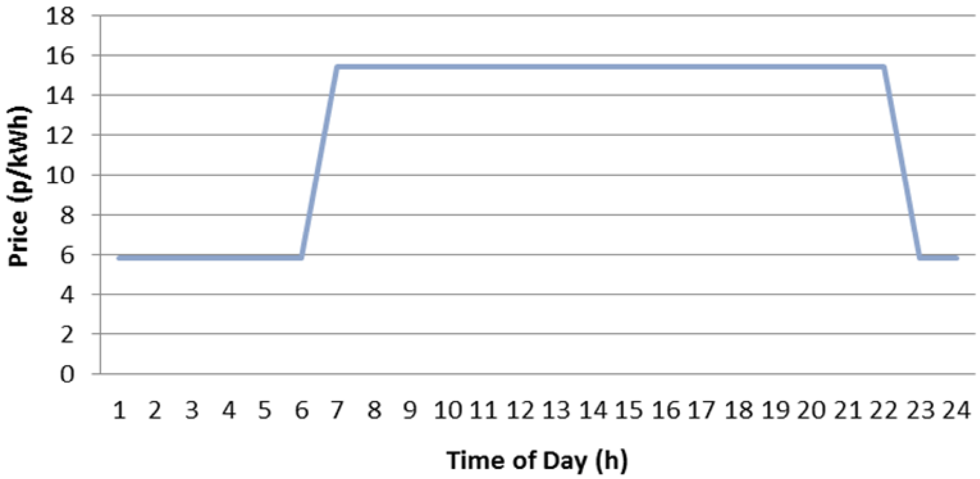
Most of the smart tariffs described above are suitable for families who are absence from their houses during peak hours. It means that this type of consumers is able to respond to the variable price signals without changing their behaviours. However, the fact has shown that families in Canada with more children will tend to “lose” under TOU pricing scheme [54].

Firstly, there is always a conflict between the less flexible electricity consumption time for most customers, like cooking times, and the consumption reduction during peak times. As shown in Figure 2-4, the usage of most household appliances is not suitable during off-peak periods. It is therefore impossible to shift load for families with children or members who have to go out for work at set times. In other words, consumers who are not able to change electricity usage habits have to pay the high rate during peak periods. As a result, the high rate during peak time may become a burden for customers instead of being a motivation for peak shaving.

Then, it cannot be ignored that smart tariffs, which help customers to manage their electricity bills by providing them more than a fixed price, enable customers’ awareness of the prices over time through smart meters. Therefore, the improvements of the smart meters require advanced two-way communication technologies and new software programs of pricing electricity. Since the cost of metering is so small compared with their electricity bill over the lifespan of the meter, the expected benefit is much higher than the cost of the meter.



(a)



(b)

Figure 2-4 (a) Electricity demand profile from an individual household; (b) Price profile for a simple TOU tariff [55]

In addition, even though there is no doubt that smart tariffs could encourage customers to respond to energy prices, the degrees of the responses and their impacts on peak demand reduction still remain uncertain. The technology and social factors, such as energy storage, web portal, in-home display, income, education, tolerance to price rise and so forth have the possibilities to affect DSR.

2.7 Chapter Summary

The chapter gives an overview of electricity tariffs and energy saving options exercised by three major suppliers in GB. They have already represented significant departure from the current flat-rate tariffs and can be broadly classified into a number of categories by their main purposes, such as tariffs for carbon emission reduction, tariffs for attracting long-term benefits, tariffs for offering economic energy for vulnerable customers and so forth.

Although they are radical improvements over the current system, their main objectives are limited to maximise its customer share. They do not fundamentally change the tariff structure for the purpose of promoting DSR to match the changing conditions between supply and load. Besides, a number of smart tariffs are introduced in this chapter. The review calls for fundamental reform in the tariff structure in the GB market to accommodate the new environment of electricity development.

Chapter 3

Smart Variable Tariff Design to Reflect Wholesale Energy Cost Variation

THIS chapter develops RTP tariffs to track energy price variation, and proposes two methods, i.e. equal interval grouping and hierarchical clustering, to convert RTP to TOU patterns. The developed tariffs are suitable for triggering DSRs in high carbon systems.

3.1 Introduction

As discussed in the last chapter, there are a number of energy products based on flat-rate tariffs in GB for domestic consumers. However, in order to provide the information of generating or purchasing electricity costs to customers to shift load from peak to trough periods, new types of smart tariffs are planned to be designed based on energy price variation in the GB wholesale market.

The pattern of RTP is firstly selected for smart variable tariff development in order to reflect energy price variation. In the following, two novel approaches are introduced to determine TOU tariffs, capturing the most significant price variations in the RTP tariffs. For the proposed TOU tariffs, the two innovative tariff design approaches adopt equal interval grouping method and hierarchical clustering method to divide a settlement day into several time intervals in order to form a TOU pattern. As to the rates of the proposed TOU tariffs, they are determined by keeping the total electricity bill for a typical domestic load profile unchanged.

In this chapter, the rationale of the proposed smart tariff designs is firstly explained. Then, eight typical energy price variation patterns are developed to represent wholesale energy price variations throughout a year. These patterns are classified by seasons and day types, and they can be converted to a series of RTP tariffs to trigger DSR. The two novel approaches used to convert the RTP tariffs to TOUs are described separately in terms of time window and rate determinations. The comparison between the results achieved by these two methods is discussed at the end of the chapter. In order to clearly state the developing process of the proposed smart variable tariffs, a flowchart of the study in this chapter is shown in Figure 3-1.

3.2 Rationale of the Proposed Smart Variable Tariff Design

As mentioned in Section 3.1, the smart variable tariffs for GB are proposed relying on RTP and TOU. The rationale of the proposed smart tariff design is described in detail as follows.

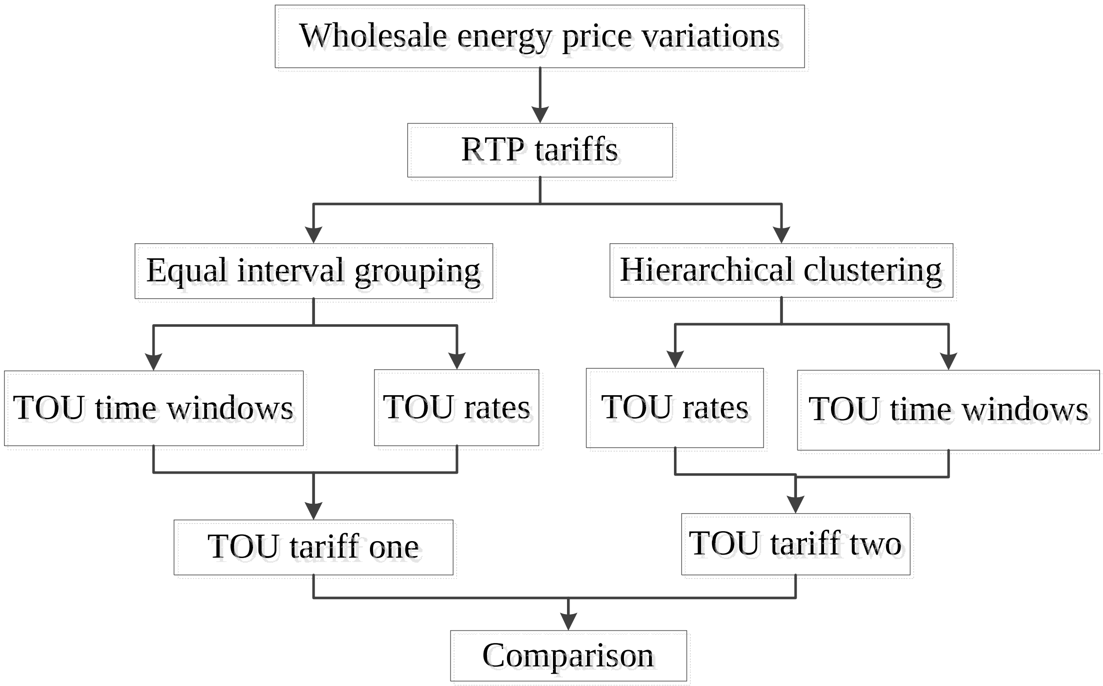


Figure 3-1 Flowchart of the investigation process in smart variable tariff design

3.2.1 Rationale of Using RTP and TOU patterns in Smart Variable Tariff Design

Wholesale energy cost, which consists of fuel procurement and operating costs together with capital cost of energy generation, is the greatest element of the household electricity bills. It covers over half of the bills according to the survey by the Office of Gas and Electricity Markets (Ofgem) [56]. Since the wholesale energy cost is still likely to be maintained as a significant part of the electricity bills in the future [30], effective responses to the energy price variation will lead to significant energy cost savings for end consumers. Potential wholesale energy cost saving could stem from avoiding fuel purchase from expensive generation plants or reducing operation time over peak periods.

In order to deliver the information of energy price variation to end-users to encourage DSR, smart variable tariffs need to be proposed following time-varying energy prices. All the TOU, CPP and RTP tariffs discussed in Chapter 2 can be taken account of in GB smart tariff development [57], and each type of tariff has its own benefits and drawbacks. Therefore, the most appropriate tariff type for smart tariff design in GB is the first issue to be considered.

The real-time dynamic pricing in the wholesale market makes a closer alignment of price with generation cost. Energy price varies every half hour in the GB wholesale electricity market [58] and a settlement day can be divided into 48 settlement periods. The illustration of energy price variation throughout a year is shown in Figure 3-2. If the change of energy price is expected to be shown to customers directly, RTP is the best pricing scheme to capture wholesale energy price variation.

However, it cannot be ignored that for general flexible load shifting in the domestic sector, RTP tariffs could scarcely guide DSR effectively since such frequent price variation is considered too complex for small electricity users [59]. This type of tariff is more appropriate to large-load consumers who enter into pre-established peak load reduction agreements [60], or to energy storage devices that can trigger DSRs by automatic operations.

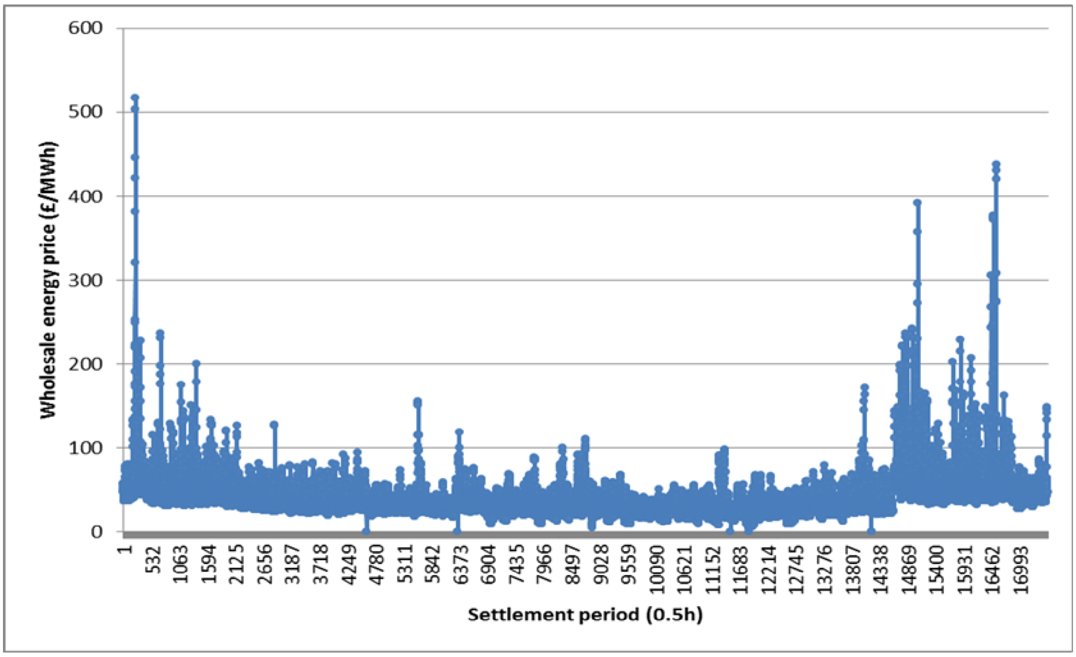


Figure 3-2 Wholesale energy price variation of 2010 [61]

TOU and CPP could provide less complex tariffs for customers because the charging period of a specified price is far longer. Although the main purpose of setting time-based pricing is to encourage customers to shift load away during high-price hours, TOU and CPP are usually set with differing rates in different time windows. CPP is mainly designed with considering the uncertainty of supply cost in power systems [48] and its critical peak periods are often associated with extremely high unit prices, which may reflect unusually high generation cost, or network congestion [62]. However, TOU enables a day to be separated into several certain fixed time periods. Accordingly, it requires relatively accurate energy price predictions and focuses on closer links to real-time energy price variation. Besides, TOU is the simplest form of variable tariff for customers to understand. Therefore, the proposed smart variable tariffs in this chapter can be extended from RTP to TOU.

3.2.2 Rationale of the Proposed Smart Tariff Design Process

1. Characteristics of energy price variation

Based on the energy price of each settlement period throughout 2010, the distribution of annual energy prices is illustrated in Figure 3-3. It can be observed that the settlement periods whose energy prices are higher than 70 £/MWh account for more than 5% of the hours in January. By contrast, in August, less than 1% of the prices are higher than 70 £/MWh. Therefore, the first characteristic of energy price variation lies in the fact that energy price varies dramatically with the change of season.

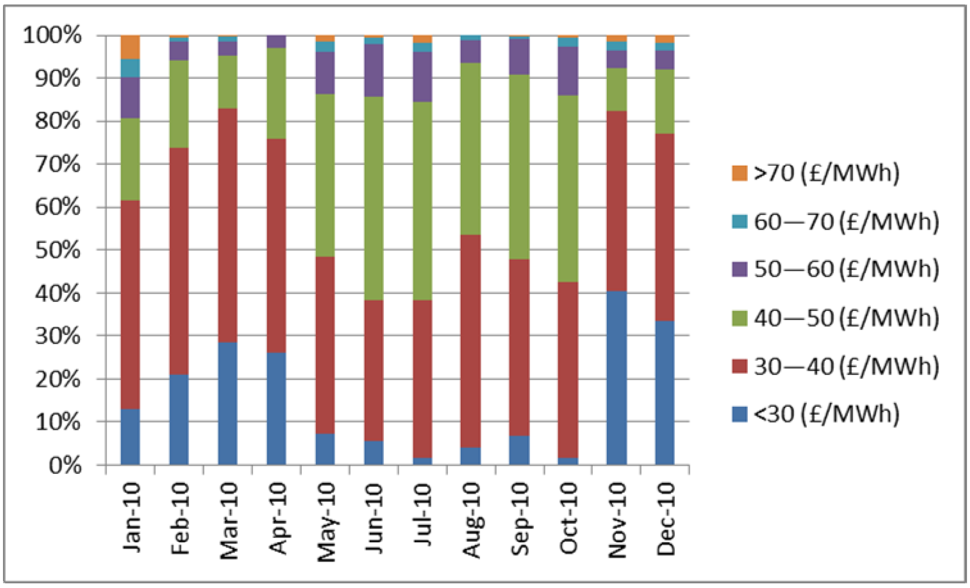


Figure 3-3 Energy price distribution in a whole year

The next task in energy price analysis is to recognize the relationship between price variation and load change. A one-day graph showing the alignment between load demand and price is drawn in Figure 3-4 where 03-Feb-2010 is selected as an example.

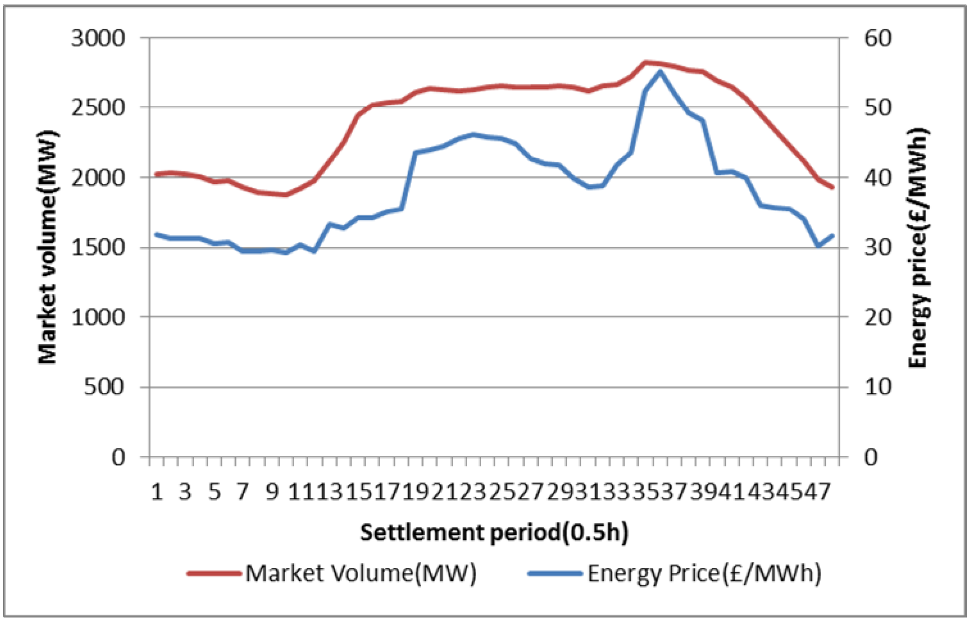


Figure 3-4 Variations of demand and energy price on 03-Feb-2010

In this instance, the demand increases dramatically from the beginning of the settlement period of 10. The morning peak demand of 2608 MW occurs at the settlement period of 19. In the following 14 settlement periods, loads level off at around 2650 MW until another increment occurs at the period of 33. The peak demand of the sample day occurs at the 35th settlement period, and the load falls to less than 2000 MW at the end of the day. The variation tendency of energy price is quite similar to that of demand. From the 10th settlement period, energy price increases gradually from around 30 £/MWh to 46 £/MWh. After a slight drop at the settlement period of 31, the peak price of 55 £/MWh occurs at the 36th period and the price falls ultimately back to 30 £/MWh.

As mentioned before, the price distribution is different in each month. Another working day of 04-May-2010, shown in Figure 3-5, is taken as the second example to explore the relationship between energy prices and demands.

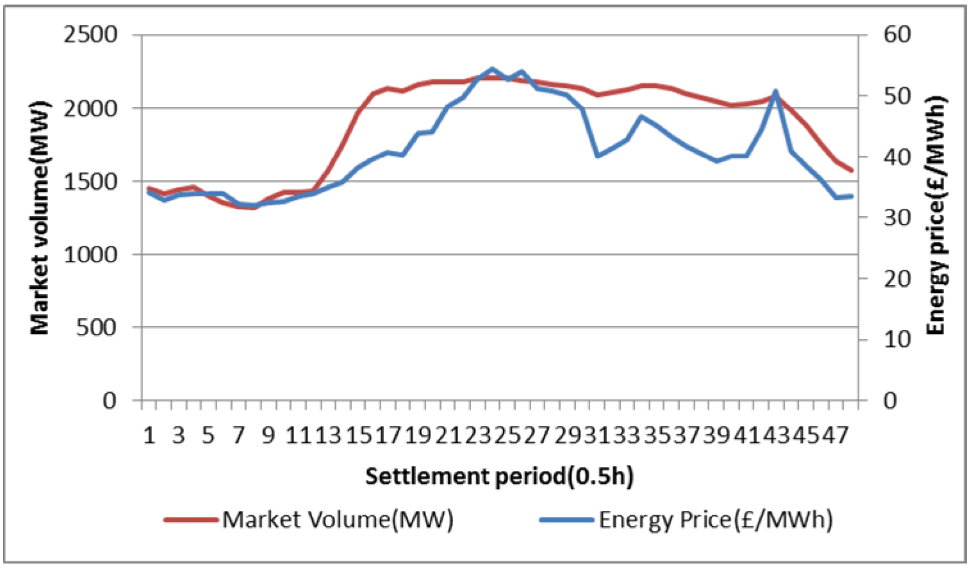


Figure 3-5 Variations of demand and energy price on 04-May-2010

The first obvious tendency of demand increment occurs at the beginning of the 8th settlement period. In this case, the demands range from 2000 MW to 2200 MW in the relatively stable period, lasting from the settlement period of 16 to 43. Eventually, the load demand returns to around 1500 MW at the end of the day. The variation of price is a little more complex than that of demand. Briefly, the energy price increases from 35 £/MWh to 55 £/MWh in the first 25 settlement periods. Then, it drops back to 40 £/MWh at the settlement period of 31. A crest of the price occurs at the 34th period and then a decreasing tendency follows. The price begins to increase again from the 39th settlement period until it reaches approximately 50 £/MWh at the settlement period of 43. Finally, the price returns to 33 £/MWh at midnight.

Even though the shapes of the profiles shown in Figure 3-4 and Figure 3-5 are not exactly the same, some similarities could still be spotted to explore the links between demands and energy prices. The peak prices and peak demands usually occur at the same settlement periods. Hence, the proposed smart variable tariff design based on energy price variation is capable of not only triggering DSR to avoid peak prices but also reducing peak demands. The conformity between energy price variation and demand change is considered as the second characteristic of energy price variation. In spite of the fact that transmission and distribution costs are not taken into consideration in this chapter, their contributions to the total electricity bill can be assumed in proportion to the contribution from energy cost.

Therefore, based on the two characteristics of energy price variation, typical energy price variation patterns developed for different seasons are able to reflect energy price change more accurately. The proposed RTP tariffs which are expected to cover the total cost of electricity can be obtained by scaling up these typical energy price variation patterns.

2. Proposed TOU tariff pattern formation

In order to achieve the proposed TOU tariffs, the developed RTP tariffs are expected to be translated into TOU patterns, which have longer time intervals to indicate the hours with relatively expensive/cheap prices [63].

A number of previous studies have been conducted on developing TOU tariffs for retail electricity markets [59, 64-66]. However, the number of price categories and time intervals for pricing are predefined and they do not explain the reasons for the proposed rates settings in TOU pricing schemes.

This chapter develops two novel approaches to determine TOU tariffs for DSR from the domestic sector. Both of them aim to successfully convert RTP to TOU without compromising too much precision. These pricing schemes are considered innovative as equal interval grouping method and hierarchical clustering method are employed to determine price blocks. The most obvious advantage of the two proposed TOU pricing schemes is that each half-hour settlement period in RTP can be classified into an appropriate price block. However, the biggest difference between them lies in whether the number of price categories in a TOU tariff is determined based upon previous experience or the clustering method.

In TOU tariff design, the settlement periods of a day can be divided into several groups with different rates [67-69], and the tariff rate of each group is determined by maintaining the total electricity bill unchanged. In other words, for a given load profile, the total bill would be the same either under the proposed RTP or TOU tariffs.

Therefore, the development process of the proposed TOU pricing schemes is summarised as:

i) Wholesale energy prices for a whole year are represented by eight typical energy price variation patterns (weekdays and weekends of four seasons)

ii) The typical energy price variation patterns are converted to eight RTP tariffs to trigger DSR;

iii) For each RTP tariff, the 48 settlement periods are grouped into appropriate price categories by equal interval grouping method and hierarchical clustering method;

iv) For each price category in TOU, the tariff rate is determined by maintaining the total bill unchanged.

3.3 Typical Energy Price Variations

Since the information of wholesale energy price over a year is essential in smart tariff design, the energy price collected from each half-hour period in any of eight day types can be represented by $p_{j,i}$ as shown in Tables 3-1.

Table 3-1 Energy prices collected from settlement periods belonging to a day type

Settlement period	1	2		48
Day 1	$p_{1,1}$	$p_{1,2}$	…	$p_{1,48}$
Day 2	$p_{2,1}$	$p_{2,2}$	…	$p_{2,48}$
Day 3	$p_{3,1}$	$p_{3,2}$	…	$p_{3,48}$
…	…	…	…	…
Day n	$p_{n,1}$	$p_{n,2}$	…	$p_{n,48}$

In this table, $p_{j,i}$ is the energy price level of the i^{th} settlement period in the j^{th} day. n stands for the number of days in one day type. For the purposes of estimating an appropriate price $p_{0,i}$ to represent generic energy price level in the i^{th} settlement period of the specific day type, a solution of $p_{0,i}$ is proposed by minimizing the sum of the squares of the distances between the estimated price and each single price. The objective function is therefore formulated as:

$$\min \ (p_{0,i} - p_{1,i})^2 + (p_{0,i} - p_{2,i})^2 + ...(p_{0,i} - p_{n,i})^2 \tag{3-1}$$

s.t. $0 < min(p_{1,i},p_{2,i}...p_{n,i}) < p_{0,i} < max(p_{1,i},p_{2,i}...p_{n,i})$

The result of $p_{0,i}$ should be within the range between the minimum and the maximum energy prices. Once the estimated energy price in each settlement period is determined, the energy price variation pattern for weekdays or weekends in a specific season is able to be obtained as $(p_{0,1}, p_{0,2}...p_{0,48})$.

3.4 Determination of RTP Tariffs

Wholesale energy cost only reflects a part of the supply cost. Other components, such as transmission and distribution costs, are expected to be added in the proposed smart variable tariffs to reflect the total cost of electricity [17]. As shown in Figure 1-2, energy costs account for 55% of the total cost of electricity. The proposed RTP tariffs are therefore determined by scaling up the obtained typical energy price variation patterns.

Therefore, similar to the typical energy price variation patterns, eight types of RTP tariffs are developed. For each RTP tariff profile, which is specifically designed for a day type, the rate in the i^{th} settlement period is

$$p_{RTP,i} = \frac{p_{0,i}}{\alpha} \tag{3-2}$$

Where the $p_{RTP,i}$ represents the rate during the i^{th} settlement period for a specific RTP tariff and α is the proportion of energy cost in the total cost of electricity.

3.5 TOU Tariff Development by Equal Interval Grouping Method

Once eight typical RTP tariff profiles classified by seasons and day types are determined by the approach mentioned in Section 3.4, the flowing task in this study focuses on the process of converting the RTP tariffs to new TOU tariffs. The eight scenarios which are classified by seasons and day types employed in the RTP tariffs continue to be used in TOU tariffs. The first approach employed for TOU tariff determination is based on quantity analysis of annual RTP prices. Accordingly, the first series of TOU tariffs can be achieved through the determinations of the following three elements:

i) TOU price categories (number of price blocks): investigate the number of price categories required to represent the variation of RTP.

ii) TOU time windows (width of each price block): based on the defined price categories, each settlement period is assigned to one of the price blocks. It is essential to determine the divided intervals per day and the duration of each time interval.

iii) TOU rates (height of price block): determine the accurate tariff rate of each price category.

3.5.1 Determination of TOU Time Windows

When RTP is translated into TOU with several pre-defined periods, the number of price categories can be obtained based on previous research. The most common TOU tariff scheme is developed with three price categories, e.g. peak, shoulder, and off-peak [67, 68]. This determination is not only because of its simplicity in form, but also due to the better use of peak and trough periods than two price blocks. The time of day is then divided into several intervals, each belonging to one of the three defined groups. In this approach, the peak, shoulder and off-peak periods are determined based on the overall price distribution of the RTP tariffs.

The equal interval grouping method is adopted for classifying the prices in the RTP tariffs. In the eight typical scenarios, each settlement period belonging to a RTP tariff is assigned to peak, shoulder or off-peak group for the forming of the required TOU pattern. The detailed grouping process is described as follows.

i) to identify the group (price block) number of the TOU tariffs. As discussed above, three-rate tariffs with peak, shoulder and off-peak periods are selected for the proposed tariff design.

ii) to determine the group interval for each group. Among all the prices in RTP tariffs, a confidence interval stated at the 95% confidence level is selected as the effective area for grouping. This range is defined as envelope for price variation. Within the valid envelope, the group interval is set equal and calculated by

$$G_{in} = \frac{E_{\max} - E_{\min}}{g_n} \tag{3-3}$$

where G_{in} is the group interval. E_{max} and E_{min} represent the maximum and the minimum prices in the envelope. The group number is denoted by g_n in price classification.

iii) to identify the price range of each group. With the increment of prices, the first group corresponds to off-peak price and peak price will be in the last group. For the k^{th} group, the maximum and the minimum prices can be obtained by

$$E_{\max,k} = E_{\max} - (g_n - k) \cdot G_{in} \tag{3-4.a}$$

$$E_{\min,k} = E_{\min} + (k-1) \cdot G_{in} \tag{3-4.b}$$

The price range of each group within price variation envelope is listed in the second row of Table 3-2. However, in order to accommodate the diversity of the initial RTP prices, the grouping results can be improved as shown in the third row of Table 3-2. The minimum allowed price in the first group can be as low as zero, and the maximum value in the last group is infinite.

Table 3-2 Price range determinations in grouping

	Off-peak	Shoulder	Peak
Initial grouping(£/MWh)	$E_{min,1}$--$E_{max,1}$	$E_{min,2}$--$E_{max,2}$	$E_{min,3}$--$E_{max,3}$
Improved grouping (£/MWh)	0-- $E_{max,1}$	$E_{min,2}$--$E_{max,2}$	$E_{min,3}$--∞

iv) to assign RTP prices of each settlement period to one of the three groups. Accordingly, the corresponding settlement periods will be assigned to peak, shoulder and off-peak periods.

3.5.2 Determination of TOU Rates

The time window determination process has been described in Section 3.5.1. It can set the TOU shape based on the price variation trend of the RTP. However, the required TOU not only contains shape information, i.e. the length of each price block, but also has information about the exact rate, i.e. the height of each block. For each rate in a TOU tariff, the most convenient way is to use the average RTP rate within the group. However, this approach is unable to express the cost variance because the load is not always flat. The average price within a group, which takes each settlement period by the same weight, would compromise the TOU's representativeness of RTP in terms of cost variance.

The rate for each price category in one of the eight day types is determined by (3-5). The idea is to maintain the total cost during the settlement periods within a group unchanged, charged by either TOU or RTP tariff. The rate is therefore achieved by

$$E_{s,k} = \frac{\sum_{t \in \mathbf{K}} e_{t,k} \cdot v_{t,k}}{\sum_{t \in \mathbf{K}} v_{t,k}} \tag{3-5}$$

Where $e_{t,k}$ stands for the RTP price of the t^{th} settlement period in group k, and $v_{t,k}$ represents the energy consumption during that period. $\boldsymbol{K}$ is the set of settlement period numbers whose corresponding RTP prices belong to group k. $E_{s,k}$ is the final obtained peak/shoulder/off-peak price.

3.6 TOU Tariff Development by Hierarchical Clustering Method

The equal interval grouping method applied for TOU tariff design has been described in Section 3.5. In that process, the number of price categories is predefined and the time windows are determined by grouping RTP prices. However, another approach of TOU tariff design employs hierarchical clustering approach to determine pricing blocks. The selected price category number, i.e. the number of clusters in this case, is an optimized value that considers the accuracy and feasibility of implementation. All the elements grouped in a cluster have the least price rate difference.

3.6.1 Proposed Methodology

By employing the clustering method, the time of a day is also divided into several intervals, each belonging to one cluster. However, this process is more complex. The flowchart illustrating breakdown steps of developing TOU by the clustering method is shown in Figure 3-6. Similar to RTP tariffs, these series of TOU tariffs are also designed for different seasons and day types.

The number of clusters required and the assignment of settlement periods in TOU largely depends on the initial RTP tariff. For example, a steady RTP can be well represented by a flat rate while a very dynamic RTP would require many different tariff rates and time intervals. In order to find appropriate clusters of the RTP without pre-knowledge, hierarchical clustering is adopted to calculate the distance between the prices of each settlement period, which indicates the similarity between periods. The initial set-up sees each settlement period being classified as its own cluster and the clusters are merged, according to similarity measures, and ultimately there is a single cluster. Based on this hierarchical clustering, a TOU tariff designed from the RTP can be achieved by the following steps:

i) For different numbers of clusters, the within-group dissimilarity is calculated. The dissimilarity is expected to decrease with the increase of clusters. After a certain number N of clusters, the decrease rate will drop significantly, which indicates much less effects with further partition. The number of clusters can be tested from 1 to the total individual settlement periods T.

ii) Each settlement period is classified into one of the N clusters so that the RTP of a typical day is divided into several time intervals.

iii) Each rate of the TOU is determined by ensuring a same cost for a typical load profile.

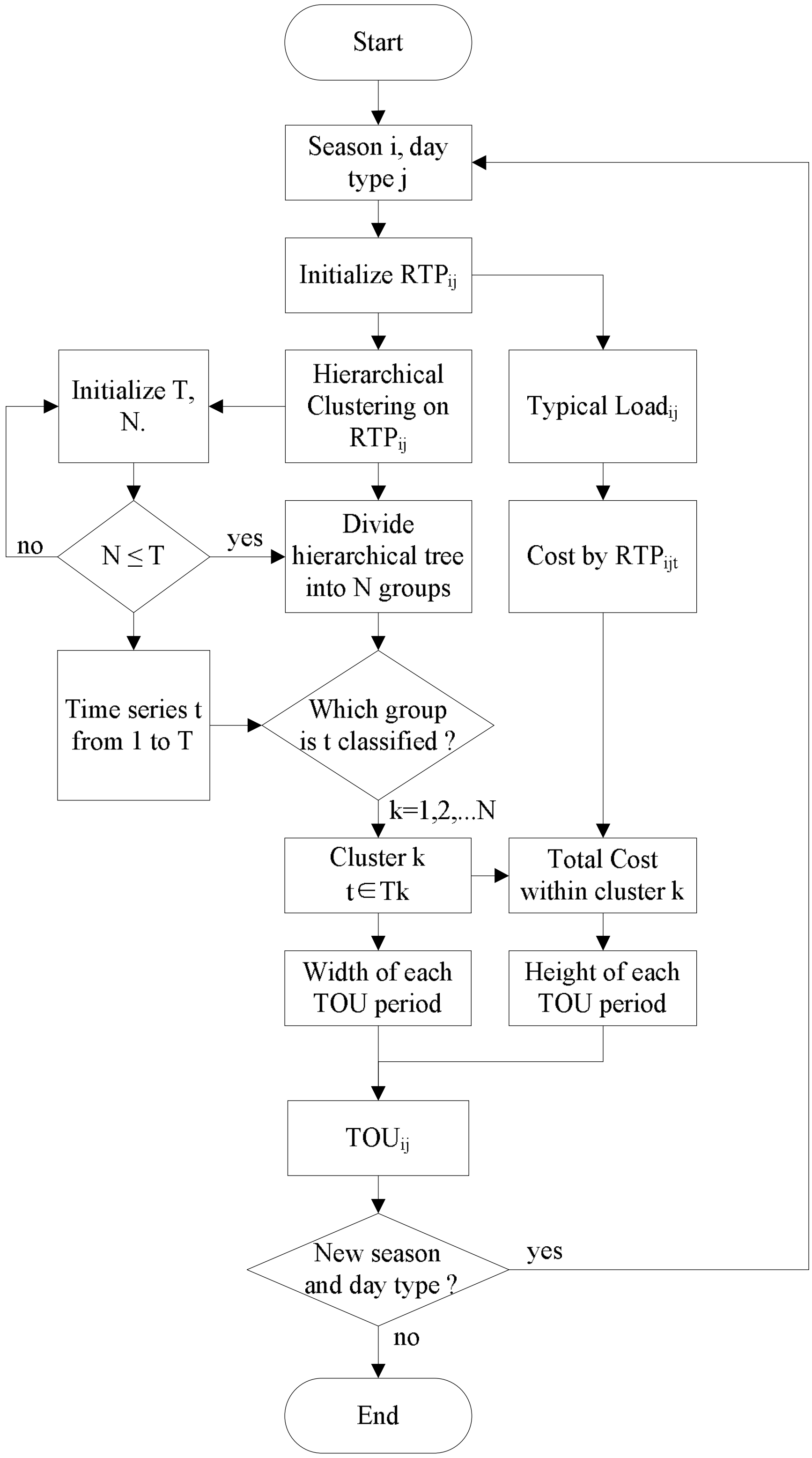


Figure 3-6 Flowchart of the development of TOU by hierarchical clustering method

3.6.2 Number of Price Categories and Time Window Determination by Hierarchical Clustering Method

For any day type, a RTP tariff can be denoted as a 1×48 vector $(p_{0,1}, p_{0,2}\ldots p_{0,48})$, and hierarchical clustering method is adopted to partition the rates of all the settlement periods into clusters. The calculation of the distances $dis_{h,f}$ between two prices $p_{0,h}$ and $p_{0,f}$ is determined by (3-6)

$$dis_{h,f} = \left\| p_{0,h} - p_{0,f} \right\| = \sqrt{\left(p_{0,h} - p_{0,f}\right)^2} \tag{3-6}$$

Where $p_{0,h}$ and $p_{0,f}$ are the prices at the h^{th} and f^{th} settlement period in the selected RTP tariff.

The next step is gathering the settlement periods into a hierarchical cluster tree by merging together those with the smallest distances on their prices. The merged settlement periods then form a cluster. After the merging process, a new distance is calculated between existing clusters and then forms new clusters [70]. The process of forming new clusters is repeated until only one cluster remains. The distances between clusters are calculated by the Ward distance in (3-7), assuming ***A*** and ***B*** are two clusters during the process.

$$dis_{A,B} = \frac{1}{|\mathbf{A}||\mathbf{B}|}\sqrt{\sum_{p_a \in \mathbf{A}} \sum_{p_b \in \mathbf{B}} (p_a - p_b)^2} \tag{3-7}$$

Where p_a and p_b are prices of settlement periods which were clustered into cluster ***A*** and ***B*** in the previous step.

3.6.3 Determination of TOU Rates

In any one of the eight TOU tariffs achieved by hierarchical clustering, the tariff rate for each cluster is presented by the quotient of the total costs under RTP and the corresponding energy consumption during all the settlement periods within the cluster, the tariff rate is then calculated by (3-8):

$$E'_{s,g} = \frac{\sum_{t \in \mathbf{G}} e_{t,g} * v_{t,g}}{\sum_{t \in \mathbf{G}} v_{t,g}} \tag{3-8}$$

where $E'_{s,g}$ is the TOU tariff rate of the g^{th} cluster, and $v_{t,g}$ represents the energy consumption in the t^{th} settlement period which belongs to the g^{th} cluster. The settlement period numbers within the g^{th} cluster are gathered in the set of $\boldsymbol{G}$. $e_{t,g}$ stands for the RTP rate in the settlement period of t.

3.7 Case Study

In order to design RTP and TOU tariffs which can reflect wholesale energy price variation, energy prices over a year are adopted for demonstration. The wholesale market data collected from [61] reflect real-time energy prices of all the settlement periods in 2010. The developed TOU tariffs achieved by equal interval grouping method and hierarchical clustering method, and RTP tariffs are shown in the following sections respectively.

3.7.1 Results of RTP Tariffs

The eventual RTP tariffs for weekdays and weekends in different seasons are illustrated in Figure 3-7 and 3-8.

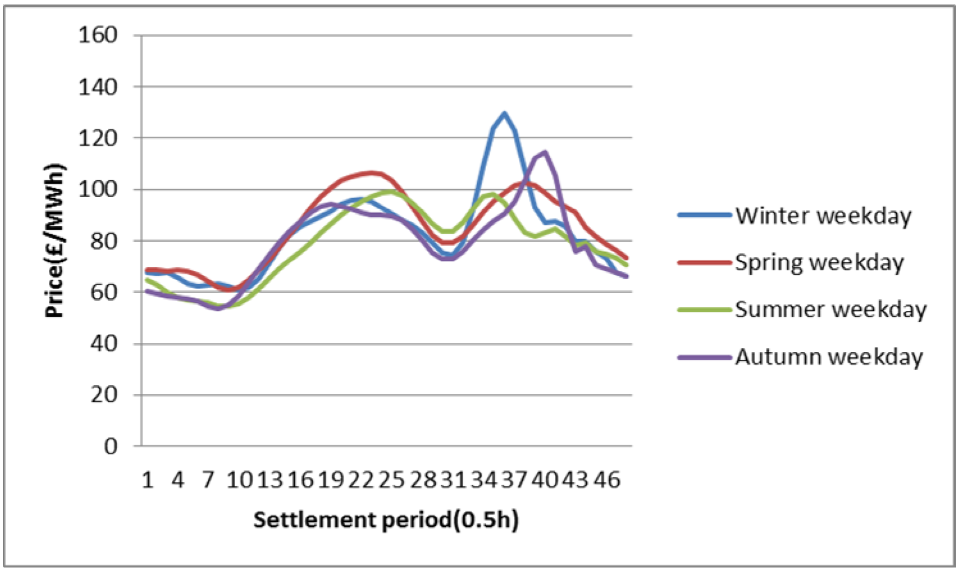


Figure 3-7 RTP tariffs for weekdays in different seasons

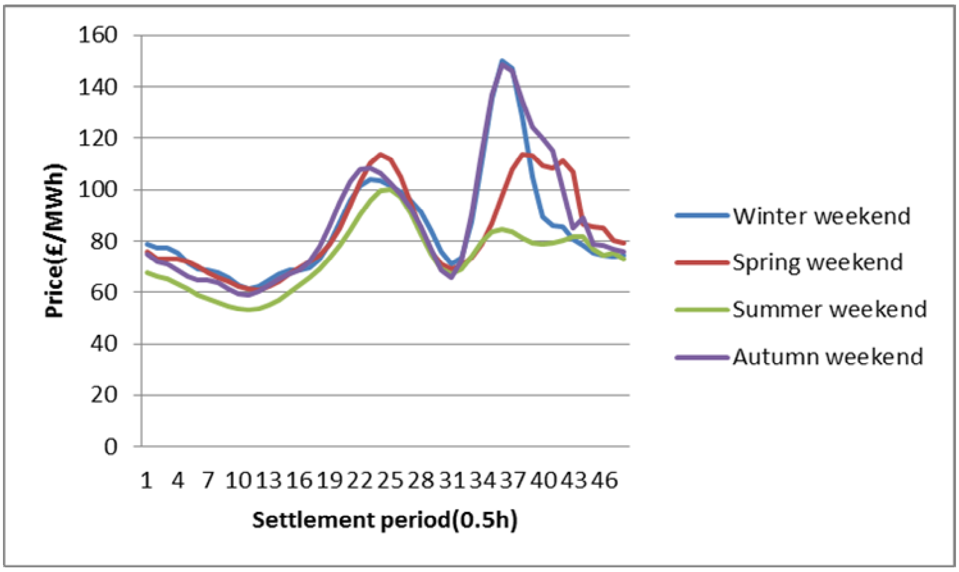


Figure 3-8 RTP tariffs for weekends in different seasons

As seen, the RTP tariffs designed for different reasons vary considerably. Peak prices generally occur in winter under both weekday and weekend scenarios. In contrast, the RTP prices in summer are much flatter. The peak price rate in summer weekdays is 76% of that in winter weekdays, and the value of the peak price in summer weekends is only 66% of the highest price in winter weekends. Overall, the RTP prices in weekends are higher than those in weekdays. Based on the achieved RTP price profiles for eight typical day types, the proposed TOU tariffs are presented in the following parts.

3.7.2 Results of TOU Tariffs Achieved by Equal Interval Grouping

In the process of TOU tariff development based on equal interval grouping, the time windows of the peak, shoulder and off-peak periods are determined, followed by the calculations of their corresponding tariff rates. These two factors are essential for the final TOU price profiles.

1. Time windows

The RTP tariffs in Figures 3-7 and 3-8 show that 95% of the price rates are within the range from 60 £/MWh to 120 £/MWh after a statistical analysis. This range is therefore defined as the envelope for price variation.

In this demonstration, the price range of each group within the price variation envelope is listed in the second row of Table 3-3, and the improved grouping results are as shown in the third row of Table 3-3 by extending the ranges of the peak and off-peak prices. Eventually, the settlement periods whose RTP prices are lower than 80 £/MWh are grouped into off-peak price blocks and the settlement periods with over 100 £/MWh prices are assigned to peak periods.

Table 3-3 Price range determinations in the case study

	Off-peak	Shoulder	Peak
Initial grouping(£/MWh)	60-80	80-100	100-120
Improved grouping (£/MWh)	0-80	80-100	100-∞

Table 3-4 Summary of the TOU tariff time windows obtained by equal interval grouping

	Peak period	Shoulder period	Off-peak period
Winter weekday	16:30—19:00	6:30--16:30 & 19:00—22:30	22:30—6:30
Spring weekday	9:00—12:30 & 18:00—19:30	6:30—9:00 & 12:30—18:00 & 19:30—23:30	23:30—6:30
Summer weekday	NA	7:30—23:00	23:00—7:30
Autumn weekday	18:30—20:30	6:30—18:30 & 20:30—22:00	22:00—6:30
Winter weekend	10:30—12:30 & 16:30—19:30	9:00—10:30 & 12:30—16:30 & 19:30—1:30	1:30—9:00
Spring weekend	10:30—13:00 & 18:00—21:30	9:00—10:30 & 13:00—14:30 & 16:30—18:00 & 21:30—0:30	0:30—9:00 & 14:30—16:30
Summer weekend	NA	9:30—14:00 & 16:30—23:30	14:00—16:30 & 23:30—9:30
Autumn weekend	10:00—12:30 & 16:00—21:00	8:30—10:00 & 12:30—14:30 & 21:00—0:00	0:00—8:30 & 14:30—16:00

By grouping the settlement periods of the eight typical scenarios, the peak, shoulder and off-peak periods for each day type are summarised in Table 3-4. All the time intervals from 1:30am to 6:30am are assigned to off-peak periods in the eight day types. Besides, there are additional off-peak periods in the late evenings of weekdays and the mid-afternoons of weekends. The peak periods do not occur in summer due to flatter tendencies of RTP variations during that season. In the remaining three seasons, peak periods are either in the late morning or the early evening.

2. Tariff rates

Typical load profiles of different day types are used to calculate total energy costs and the price rates in TOU tariffs. In the case study, generic GB domestic load profiles [29] of weekdays and weekends are employed and their shapes are shown in Figures 3-9 and 3-10 separately.

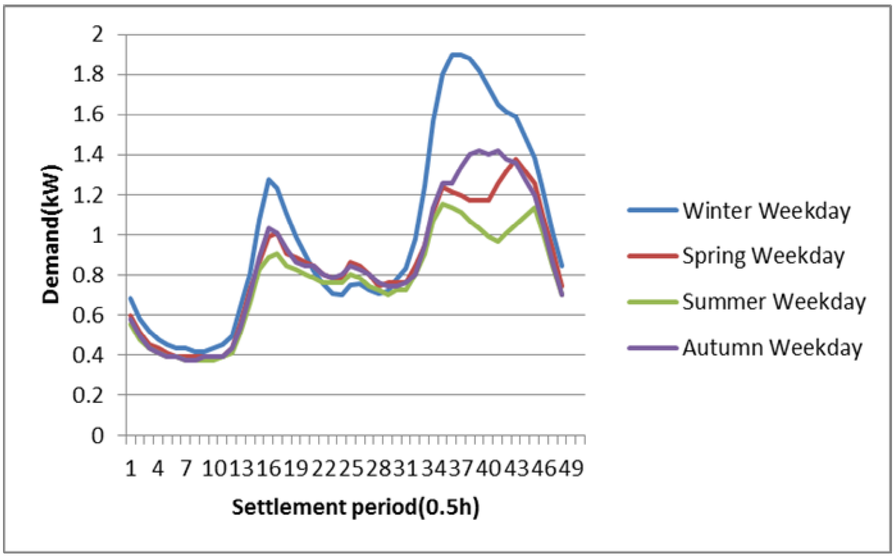


Figure 3-9 Typical domestic individual load profiles for weekdays

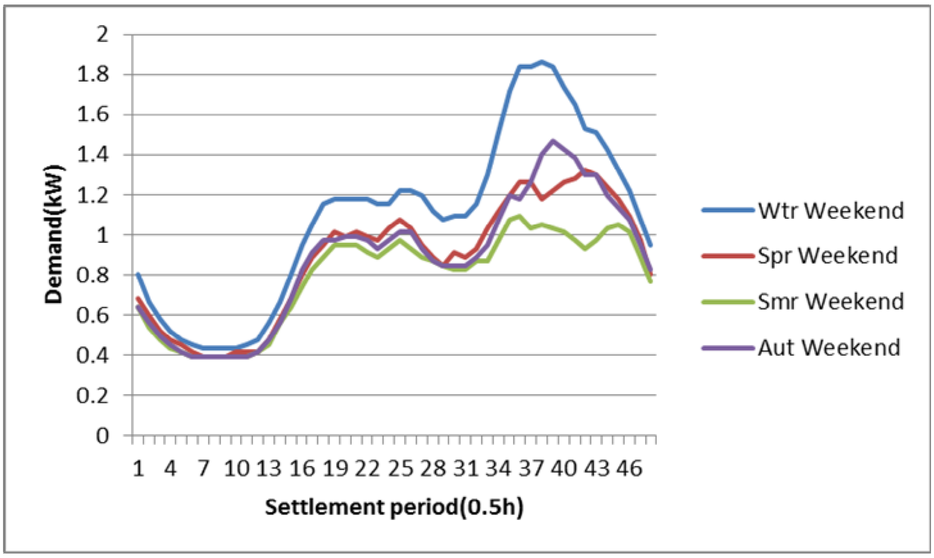


Figure 3-10 Typical domestic individual load profiles for weekends

The calculated tariff rates are summarised in Table 3-5. The highest rate in the proposed TOU tariffs is 121.89 £/MWh, which occurs at winter weekends. In contrast, the cheapest price during the off-peak periods is 63.55 £/MWh at summer weekdays. Overall, both the off-peak prices and shoulder prices for the eight typical day types vary insignificantly. All the off-peak rates stay within the range from 63 £/MWh to 70 £/MWh, and the shoulder prices vary between 82 £/MW and 89 £/MWh. The peak prices in winter are generally much higher than those in spring and autumn, and there are even no peak rates set for summer weekdays and weekends.

Table 3-5 Summary of the TOU tariff rates obtained by equal interval grouping

TOU rate (£/MWh)	Off-peak rate	Shoulder rate	Peak rate
Winter weekday	66.54	86.03	118.66
Spring weekday	67.46	88.50	103.27
Summer weekday	63.55	86.94	--
Autumn weekday	64.99	86.25	108.96
Winter weekend	68.35	82.82	121.89
Spring weekend	69.26	85.05	109.46
Summer weekend	65.02	83.81	--
Autumn weekend	67.30	84.32	118.98

3. TOU tariff profiles

Once the tariff rates for peak, shoulder and off-peak periods in each settlement day are calculated following the determinations of TOU time windows, the TOU tariffs for weekdays and weekends in different seasons can be plotted as shown in Figures 3-11 and 3-12. They are alternatives to the RTP tariffs for potential load shifting.

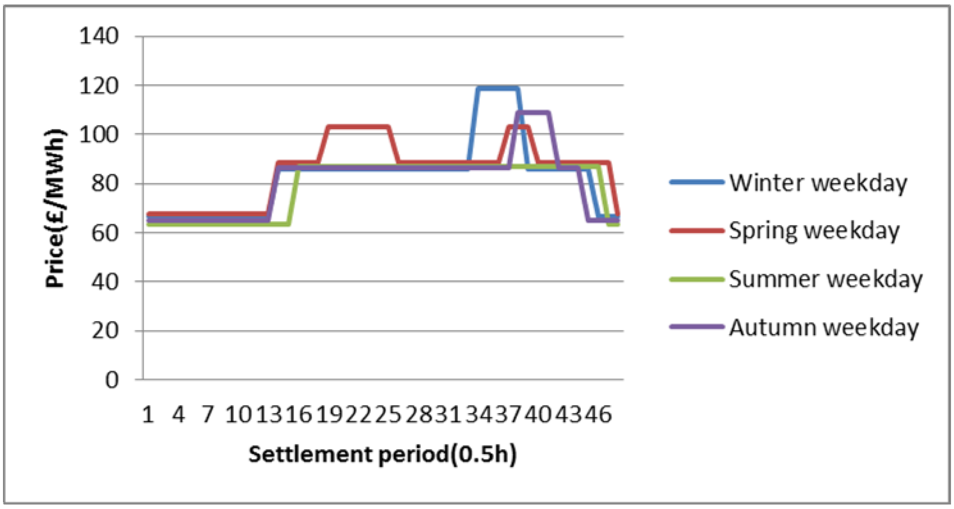


Figure 3-11 TOU tariffs for weekdays in different seasons obtained by equal interval grouping

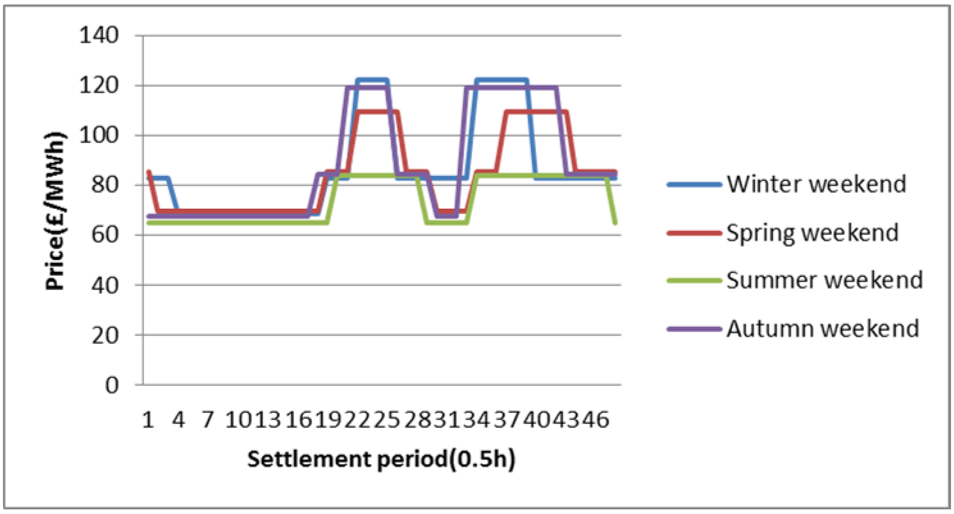


Figure 3-12 TOU tariffs for weekends in different seasons obtained by equal interval grouping

Based on the TOU price profiles designed for weekdays, it can be observed that the off-peak price rates and durations in weekdays are roughly the same for all the eight scenarios. However, the situations are totally different for peak periods. Two time intervals make up peak periods in a typical spring weekday, but none of the settlement periods in a summer weekday are assigned to peak categories. Even though both winter and autumn have a time interval for peak price, the degrees of price levels and durations in winter are much higher than the degrees in autumn. Compared with the TOU tariffs designed for weekdays, the TOUs for weekends have longer peak periods. Besides, two peak time intervals which occur in the morning and evening respectively are designed for all typical weekends except in the summer.

3.7.3 Results of TOU Tariffs Achieved by Hierarchical Clustering Method

1. Number of clusters

For each number of cluster, the average within-group distance [71] is calculated. The lower average within-group distance indicates a higher similarity within the group. The distance changes with the number of clusters within winter weekdays are listed in Table 3-6 as an example. The changes in other scenarios are shown in Appendix A.1.

For a typical winter weekday, when the prices of all the settlement periods are grouped in 1 cluster, the within-group distance is very high at 47. It starts to decrease when similar prices are categorised in clusters, decreasing quickly to 5.61 at 3 clusters, and further partition only gives slight improvement. For other day types, the decreases also become much slower when the number of clusters are larger than 3. Therefore in the design of TOU, 3 price categories would be sufficiently representative for all the eight scenarios.

Table 3-6 Average within-group distance along different number of clusters

Cluster	Average within-group distance (£/MWh)
1	47
2	17.64
3	5.61
4	3.29
5	2.21
6	2.44

2. Time windows

Taking the winter weekdays as an example as well, each settlement period can be assigned into one of the three clusters, i.e. peak, shoulder and off-peak. As shown in dendrogram of Figure 3-10, the 48 settlement periods of RTP are clustered based on their price distance, which is reflected in the height of the y-axis. Three clusters will be partitioned as shown in the red boxes of the figure.

The dendrograms of the hierarchical clustering in other day types are shown in Appendix A.2. Accordingly, the TOU time windows obtained by the clustering method are summarized in Table 3-7.

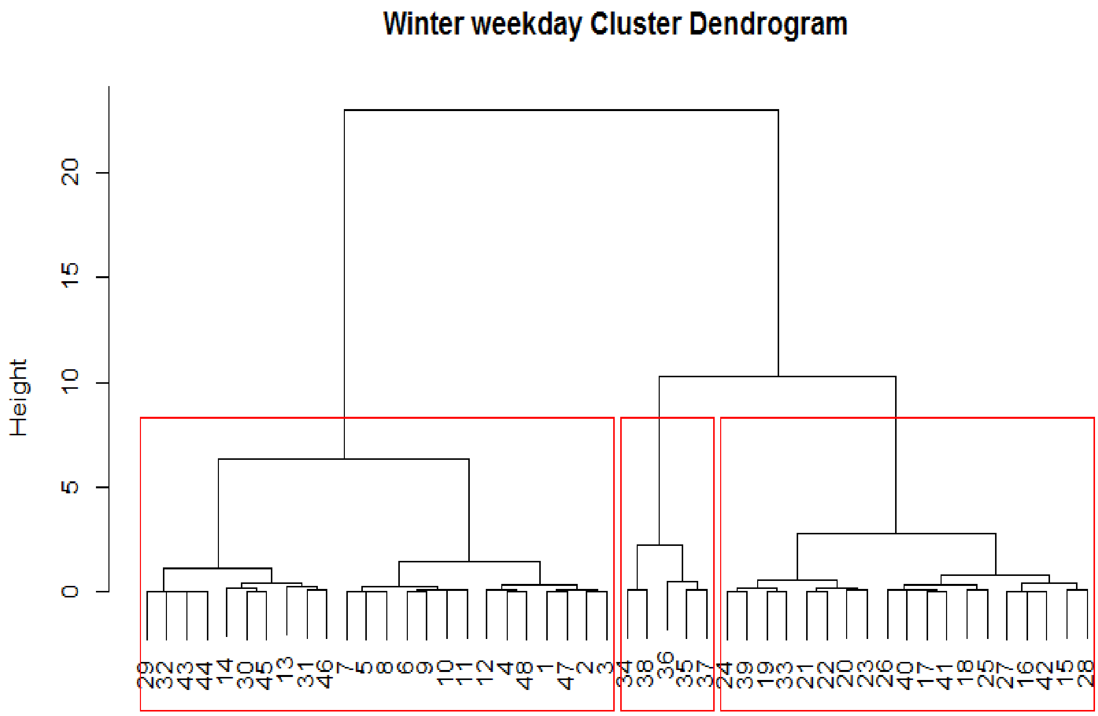


Figure 3-13 Hierarchical clustering for real time prices intervals

The clustering process has determined the number of clusters and their corresponding time intervals. It can set the overall shape of the TOUs following the variation trends of RTPs. As seen in Table 3-7, each RTP tariff is converted into a TOU pattern with three price steps, including the RTPs for summer weekdays and summer weekends. By employing the clustering method, the settlement periods overnight are still assigned to off-peak price blocks. In the RTP tariffs, prices in winter weekdays and weekends are generally higher than those in other seasons. However, the durations of peak periods in winter are shown as being not as long as those in three other seasons. The reason for the shorter peak periods in winter is that the settlement periods with critical high RTP prices mainly contribute to the peak periods in TOU. Due to the large gaps between the critical high prices and other prices, all the settlement periods with non-critical prices are assigned to shoulder or off-peak periods.

Table 3-7 Summary of the TOU tariff time windows obtained by hierarchical clustering

	Peak period	Shoulder period	Off-peak period
Winter weekday	16:30—19:00	7:00--14:00 & 19:00—21:00	21:00—7:00 & 14:00—16:30
Spring weekday	8:00—13:30 & 16:30—21:30	6:00—8:00 & 13:30—16:30 & 21:30—0:00	0:00—6:00
Summer weekday	10:00—13:30 & 16:00—18:00	6:30—10:00 & 13:30—16:00 & 18:00—0:00	0:00—6:30
Autumn weekday	7:00—13:30 & 16:30—21:00	5:00—7:00 & 13:30—16:30 & 21:00—0:00	0:00—5:00
Winter weekend	16:30—19:30	10:00—13:30	13:30—16:30 & 19:30—10:00
Spring weekend	10:30—13:00 & 18:00—21:30	9:00—10:30 & 13:00—14:00 & 16:30—18:00 & 21:30—0:00	0:00—9:00 & 14:00—16:30
Summer weekend	9:30—14:00 & 16:30—22:30	7:30—9:30 & 14:00—16:30 & 22:30—2:00	2:00—7:30
Autumn weekend	17:00—19:00	9:00—14:00 & 16:00—17:00 & 19:00—22:00	14:00—16:00 & 22:00—9:00

3. Tariff rates

The calculated tariff rates are listed in Table 3-8. Different from the results in Table 3-5, the tariff rates in the eight scenarios vary dramatically from one to another, no matter if they are for peak, shoulder or off-peak periods. In detail, the difference between the off-peak rate at winter weekends and that at summer weekends is 20.25 £/MWh. Meanwhile, the shoulder price rate in autumn weekends is 1.4 times of that in autumn weekdays, and the peak rate in summer weekends is only 65% of that in winter weekends.

Table 3-8 Summary of the TOU tariff rates obtained by hierarchical clustering

TOU rate (£/MWh)	Off-peak rate	Shoulder rate	Peak rate
Winter weekday	73.34	89.24	118.66
Spring weekday	66.07	81.07	98.40
Summer weekday	59.20	80.79	96.11
Autumn weekday	57.40	73.72	94.44
Winter weekend	77.25	100.19	129.92
Spring weekend	69.93	86.07	109.46
Summer weekend	56.60	70.00	84.70
Autumn weekend	70.74	102.49	141.24

4. TOU tariff profiles

The results of the TOU tariffs developed based on hierarchical clustering method show eight price profiles in Figure 3-14 and 3-15. In each day type, the developed TOU tariff is designed with three price-steps. It is obvious that the results of the TOU tariffs are different from each other in terms of time window duration and tariff rate level. For the peak, shoulder and off-peak prices, the lowest rate occurs at summer weekends and the highest is at winter weekends.

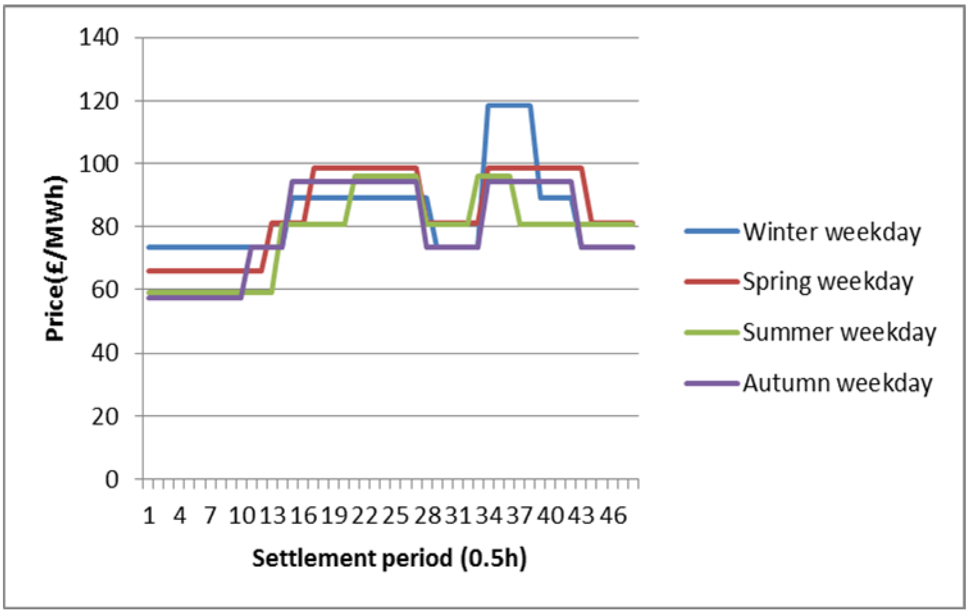


Figure 3-14 TOU tariffs for weekdays in different seasons obtained by hierarchical clustering

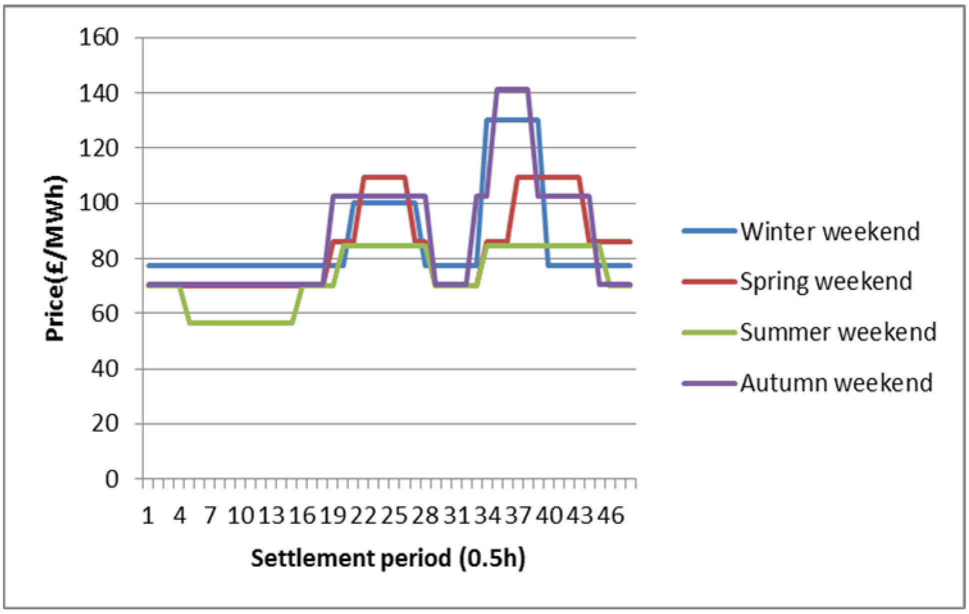


Figure 3-15 TOU tariffs for weekends in different seasons obtained by hierarchical clustering

3.8 Discussion

The two TOU design approaches described above aim to transfer the variable price signals which change frequently over time into flatter price signals for easier DSR. The results have shown that the RTP tariffs, under all the scenarios, can be represented by TOUs with three tariff rates and no more than eight time intervals per day.

In these two approaches, the first method determines TOU tariff time windows depending on the distribution of RTP prices throughout a year with equal interval grouping. The number of price categories is determined according to previous study of TOU tariffs. Besides, the settlement periods are classified into different groups based on a valid price variation envelope. Therefore, the time window can be determined without the perturbations of critical peak or trough energy prices.

The second method, which employs hierarchical clustering, presents the first attempt to determine price categories and time intervals for TOU with high statistical confidence, and it is able to put the settlement periods with similar prices into a cluster. At the same time, this approach provides a solid theoretical foundation in mathematics for the TOU pricing scheme. However, when critical peak or critical trough price in RTP tariffs occurs, this approach may be not sensitive in distinguishing other settlement periods to different groups.

For the TOU tariffs developed by grouping annual prices, peak periods only occur in winter, spring and autumn. Even though the peak rates in different scenarios are distinct from each other, there is no obvious difference in the tariff rates between different seasons. The developed TOU tariffs by the hierarchical method have completely different results in terms of time windows and tariff rates. Since this approach focuses on the price variation within a typical day, there are obvious distinctions between the TOU price profiles for different scenarios.

3.9 Chapter Summary

This chapter proposes a RTP tariff design approach and two methods to develop TOU tariffs from the obtained RTP tariffs using equal interval grouping and hierarchical clustering techniques. The demonstration results prove that the developed TOUs can reflect the variation of real-time energy prices in the wholesale market with less price rates.

Generally, the smart variable tariffs designed based on real-time energy prices are expected to encourage customers to shift their loads in response to the price variations. In high carbon systems where the variation trends of distribution charges and energy costs are the same, the responses to the proposed RTP and TOU tariffs in this chapter can lead to peak demand reduction together with wholesale energy cost saving. The developed smart variable tariffs would be applied to trigger response enabled by energy storage or demand shifting for future energy management.

Last but not least, all the RTP and TOU tariffs are achieved depending on a significant factor, i.e. the percentage of energy cost in the total electricity bill. In practice, this value may not appropriate for all the situations in GB. Therefore, future smart variable tariffs can be improved by scaling up or down the obtained results to accommodate real situation.

Chapter 4

Active Demand Response Enabled by Shared Battery and Smart Variable Tariffs

THIS chapter develops a novel methodology for DSR and home area energy management, using shared energy storage and smart variable tariffs.

4.1 Introduction

Chapter 3 has developed a number of smart variable tariffs to reflect energy price variation and encourage DSR. However, common behaviours of DSR, such as using appliances and heating water at night, compel consumers to change their daily life behaviours greatly. In order to minimise the impact of DSR on the normal lives of customers, distributed energy storage can be adopted as an alternative way to trigger DSR.

In a deregulated market, wholesale energy costs and distribution investment costs contribute significantly to consumers' electricity tariffs. However, in a low carbon electrical power system, the two cost pressure points may not be synchronous in time and space with each other. To accommodate this asynchrony, this chapter develops a novel methodology for home area energy management as a key vehicle for DSR, using electricity storage devices. The aim is to enable energy storage at consumer premises to not only take advantage of lower wholesale energy prices, but also to support LV distribution networks for reducing network investment. New operation strategies for domestic energy storage to facilitate DSR are developed in the chapter. They have the capability to maximise the overall savings in energy costs and investment costs.

In the proposed approach, the operation of home-area energy storage devices is jointly conducted by end customers and network operators. The purpose is to explore an optimal balance between DSRs to energy price and to network congestion, and thus to maximise benefits for both consumers and network operators. An intensive study is carried out to investigate the impacts of different dispatch strategies on wholesale energy costs and network investment costs. Benefit quantification methods are introduced as well to evaluate the total benefits in terms of savings in energy costs and investment costs that can be brought along by the proposed operation approach. The demonstration is carried out on two practical distribution networks with varying utilisation levels for one typical calendar day and a whole year.

4.2 Problem and Proposed Solution Statement

Energy storage systems, such as pumped hydroelectric energy storage (PHES), have been in use since 1929 to provide energy and ancillary services [72]. Energy storage can store energy when there is less demand and release the stored energy back to the system during peak periods. This feature of energy storage makes it an ideal candidate to facilitate domestic (a.k.a. residential) DSR, by which households vary electricity demand due to changes in the balance between supply and demand at the right times. Proper DSR can effectively optimise energy consumption to reduce wholesale energy costs, minimise the impact to infrastructure networks and then eventually reduce electricity bill.

Domestic DSR can play a critical role in reducing the pressures in wholesale energy market and network infrastructure, particularly at LV distribution level. Investigations show that LV network costs bear the highest impact from domestic DSR [73]. Domestic DSR enabled by an integrated home area energy and storage management system has the potential to offer great flexibility in response to pressure points across the systems. However, the application of energy storage in LV networks to date is still limited due to:

i) the installation costs of storage devices are very high and costs are entirely born by consumers;

ii) the devices are largely used to save energy costs rather than to offer support to the needs of network operators, making it economically unattractive.

This situation is changing with the evolutions in material science and power systems:

i) the costs of small-scale energy storage devices drop significantly [74];

ii) smart grids provide physical infrastructure to enable energy storage devices to supply system-wide support for different parties [75].

These positive developments have motivated energy storage to facilitate the implementation of domestic DSR.

Theoretical and practical implementation of DSR enabled by energy storage in response to energy price variation has been discussed in earlier publications [76-79]. These efforts focused on developing operation strategies of energy storage to facilitate DSR in response to merely energy prices and/or renewable production. However, the impact of DSR on network investment is not considered. The major disadvantage is that in a low carbon system, low energy prices as a result of sufficient renewable energy might coincide with high demand. Therefore, if domestic DSR is entirely employed to respond to the smart variable tariffs for the purpose of energy cost reduction, it might lead to overloading along networks particularly at LV level. Papers [80, 81] investigated the impact of DSR facilitated by energy storage devices on residential load profiles. They, however, neither considered the consequential impact on wholesale energy cost nor on distribution networks.

This chapter proposes an innovative shared ownership of battery utilization between domestic customers and local network operators. The energy storage devices are physically installed at households. They can be entirely or jointly operated by customers and network operators in response to both wholesale energy prices and network conditions, called multi-service energy storage. New operation strategies are developed thereby to dispatch the energy storage. The developed model allows domestic energy storage to dynamically respond to pressures in energy prices and network conditions in order to further obtain savings in energy costs and network investment. The potential benefits from introducing joint ownership and dynamic dispatch of domestic energy storage are quantified, in terms of:

i) energy cost savings for customers;

ii) network investment deferral for system operators.

The quantification is operated in three steps:

i) to benchmark the benefits using traditional approaches, where the storage devices are entirely owned and controlled by customers;

ii) to quantify the benefits from static shared ownership, where the ownership share is predetermined and fixed over a given period;

iii) to quantify the benefits from a dynamic ownership of energy storage where the ownership dynamically changes over time.

The proposed methodology is demonstrated on two practical networks taken from UK distribution systems.

Compared to existing work on household energy storage operation, this work has the following four key contributions:

i) it proposes a novel concept of sharing the ownership of household energy storage between customers and network operators. The benefits are that the energy storage can not only respond to energy price variations but also to network conditions;

ii) it designs a new dynamic operation scheme for the jointly operated energy storage. The operation scheme can properly operate energy storage to meet the needs of customers to reduce energy costs and of network operators to reduce network investment costs;

iii) it introduces new quantification methodologies to evaluate the benefits that the shared energy storage can bring forward over one year in terms of savings in energy cost and network investment;

iv) it quantifies the benefits of energy storage applied to actual systems under both prefixed operation mode and dynamic operation model and investigate how the changes in network conditions affect the resultant benefits.

The remainder of the chapter is organised as follows: Section 4.3 details the rationale of using multi-service energy storage. Section 4.4 introduces energy storage operation strategy over one day, and annual energy storage dispatch strategy is further investigated in Section 4.5. In Section 4.6, the approaches for quantifying network investment and benefits of using household energy storage are presented. Section 4.7 demonstrates the shared ownership of household energy storage over the status quo on practical systems. Conclusions are drawn in Section 4.8.

4.3 Rationale of Using Multi-service Energy Storage

Energy prices and system load levels are traditionally closely linked: when system demand is high, energy prices are also high as marginal generation tend to be from more expensive fossil-fired generators. This is no longer the case in a low carbon system: when system demand is high, which means the network is more likely to be congested, energy prices could be low if cheap renewable energy is abundant. Figure 4-1 shows two possible relationships between energy prices and system demand levels in a smart grid system: conforming case and conflicting case. In the conforming case, the variation of energy price is similar to the variation of demand. This type of case is very common in current electrical systems dominated by fossil-fired generation. On the contrary, in the conflicting case, the variations of energy price and demand have opposite trends [82]. In this case, if household energy storage is dispatched entirely in response to wholesale energy prices, it could further increase system congestion.

Traditional operation strategies of energy storage devices only control them to facilitate DSR in response to wholesale energy price variation, defined as single-service operation schemes. They did not explore the potential benefits of energy storage to reduce network investment costs.

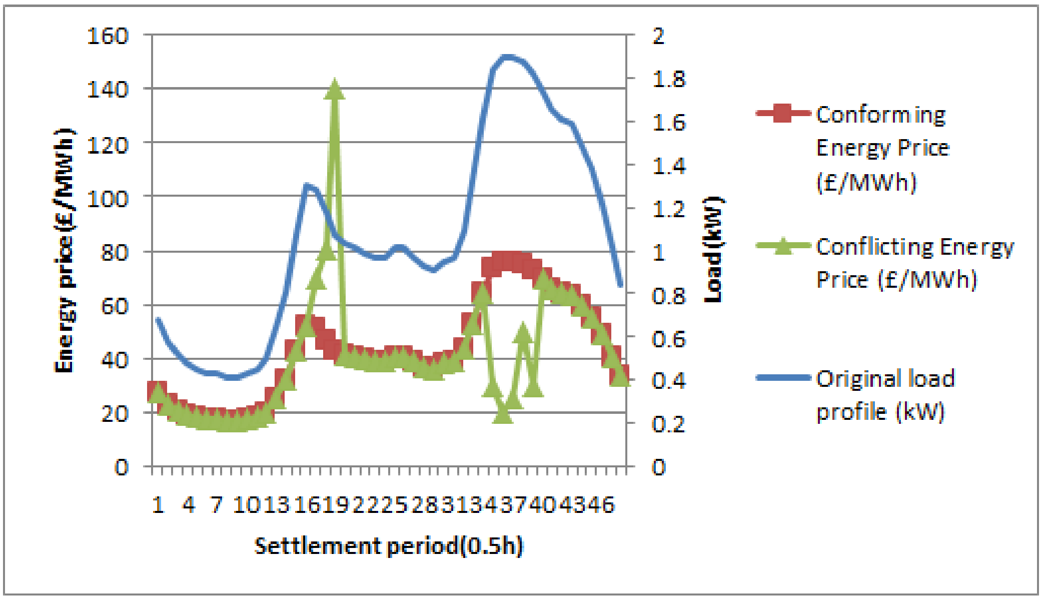


Figure 4-1 Typical energy price and household load profiles of a day

This chapter introduces a new multiple-service operation strategy for household energy storage devices realised by joint ownership. The devices are accessible to both customers and network operators and they can control part of the devices to serve their needs. Domestic customers can control part of the storage in response to energy prices mobilized by smart variable tariffs in RTP forms, and network operators can control the other part in response to network conditions. By doing so, customers can reduce their energy costs by shifting demand to the period with low energy price while network operators can reduce/defer needed network upgrades by shaving system peak demand. Such a new operation scheme can resolve the potential conflicts between energy prices and network conditions as a result of high intermittent generation penetration. It can help the implementation of domestic DSR to maximise the utilisation of both renewable energy and network infrastructure.

4.4 Energy Storage Operation Strategy

Conventional domestic energy storage control was conducted by a single operator. The only informing signal is short-term spot price and the operation algorithms are for reducing energy costs only. Their implementation steps can be generally summarised as:

i) to find the periods with the highest electricity prices as discharging time slots;

ii) to find the periods with the lowest electricity prices as charging time slots;

iii) to decrease the electricity usage at discharging periods and increase it at charging periods until the stored energy is completely released or the storage is fully charged.

In order to maximise the benefits of introducing energy storage into LV distribution systems, the operation strategies need to be improved using joint ownership between customers and DNOs to facilitate their different purposes. The concept is detailed in Figure 4-2. The variable "*x*" represents the percentage of storage capacity controlled by customers and the rest capacity *(1-x)* is controlled by operators. The challenge therefore is to develop an effective and efficient operation strategy for energy storage to achieve the concept.

This section is divided into three parts to devise one-day operation strategy: domestic demand profile modelling, storage battery configuration, and static energy storage operation strategy.

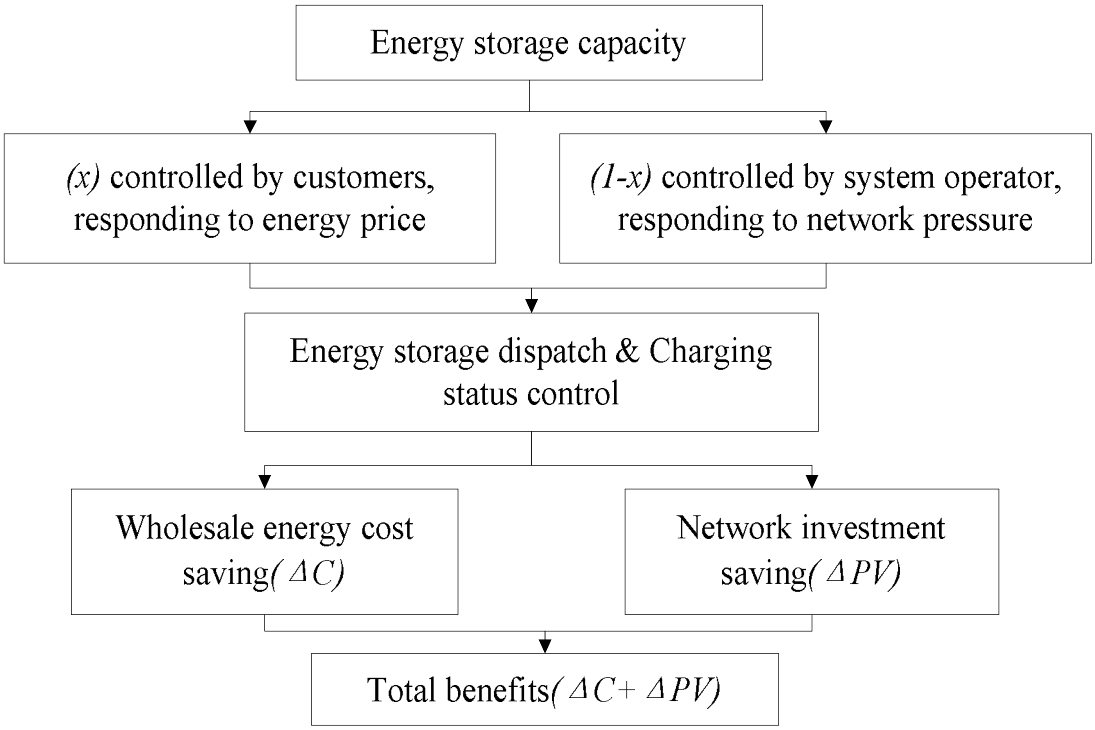


Figure 4-2 Flowchart of energy storage dispatch

4.4.1 Domestic Demand Profile Modelling

As the majority of electricity trading volume can be forecasted 24 hours ahead [83, 84], one-day ahead load profiles are adopted for the management of joint ownership energy storage. In this study, a calendar day is divided into 48 half-hour settlement periods in order to reflect the variations of demand. The profile of a typical household demand in a day is represented by a 48×1 column vector $\boldsymbol{L}_{\mathrm{or}}$. Similarly, the energy prices of a day are represented by a 1×48 row vector $\boldsymbol{Ee}$.

As the impact of DSR and energy storage management will be analysed at distribution network level, it is necessary to build load profiles at substations, which are the aggregation of individual load profiles served by a substation. In order to reflect the diversity in load types, five classes of typical domestic load profiles, stemmed from typical eight generic profile classes [29], are manipulated to model the plethora of different metering configurations. These five profiles differ in peak load times, which appear at 16:00, 17:00, 18:00, 19:00 and 20:00 respectively. Each load profile of the five represents a type of household in real life. They, defined in National Statistics of UK, are derived from a large volume of real household data [85]. The five percentages are 13%, 19%, 30%, 26% and 12% respectively, which roughly follow Gaussian distribution, as given in Figure 4-3. Therefore, the percentage of each household type is chosen as the percentages of profile classes 1-5. This selection of profile distribution will be sufficiently reasonable from the aspects of social survey and mathematical normal distribution.

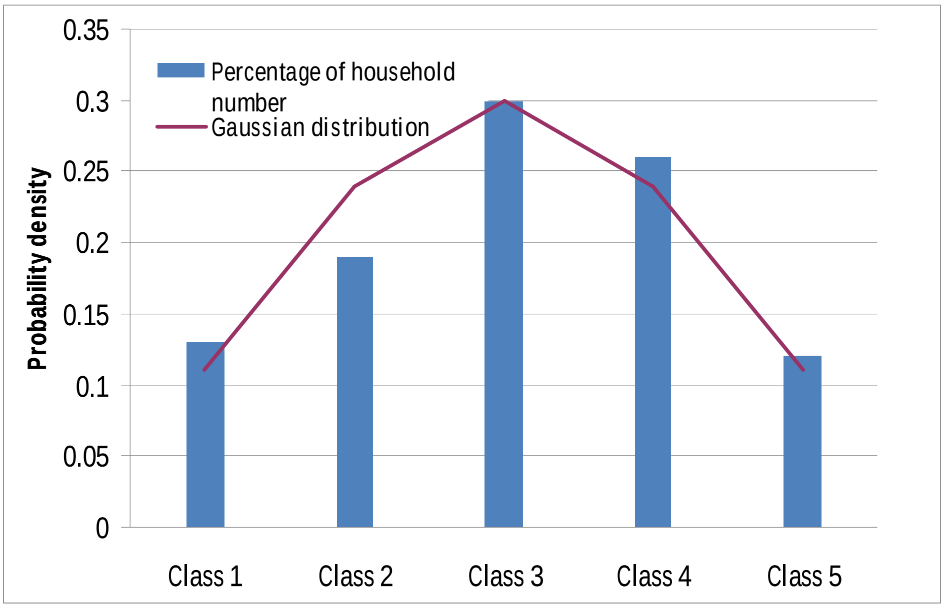


Figure 4-3 Probability distribution of household numbers

A bottom-up approach is employed to estimate the demand profiles at substations. Household load profiles are first chosen from the typical profiles and then aggregated together. The load profile at substation level can be estimated by

$$\mathbf{L}_{system} = \sum_{k=1}^{5} \mathbf{L}_k \cdot N \cdot K_k \tag{4-1}$$

where, L_k is the k^{th} class of the typical load profile; K_k is the percentage of the household with the k^{th} profile. N represents the household number supplied by a substation.

The five typical household load profiles together with the resultant aggregated unit profile are depicted in Figure 4-4.

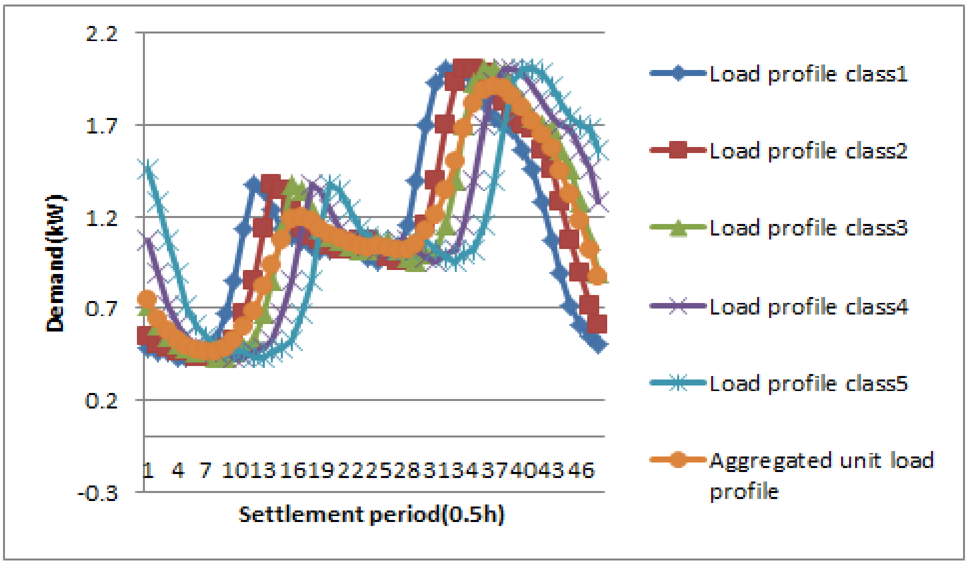


Figure 4-4 Daily household load profile types and aggregated unit profile

4.4.2 Storage Battery Configuration

Energy storage discussed before is realized by storage battery. The battery configuration referenced here consists of 4×50Ah 12V battery cells, which are connected together to form home-area energy storage [86]. Only five combinations/scenarios with different share between customers and DNOs can be achieved with the four identical battery cells. The five scenarios are defined in Table 4-1, where Scenario 1 is chosen as benchmark scenario. One or more than one scenario from the five will be selected for charging and discharging actions in the following prefixed dispatch and dynamic dispatch strategies.

Table 4-1 Five defined dispatch scenarios

Scenario	Storage capacity controlled by customer (%)	Storage capacity controlled by DNO (%)
1	100	0
2	75	25
3	50	50
4	25	75
5	0	100

4.4.3 Energy Storage Dispatch under Fixed Operational Share

Under this scenario, it is assumed that x ($0 \le x \le 1$) of energy storage capacity is controlled by customers to respond to energy prices and the rest capacity is operated by DNOs to shave household peak demand. For the shared capacity controlled by customers, the threshold for charging and discharging t_p is assumed to be an energy price. The settlement periods whose energy prices are lower than t_p are chosen as charging candidate periods and the periods with prices higher than t_p are treated as discharging candidate periods.

The proper setting of t_p is important due to that it could affect the operation cycles of energy storage. The optimal threshold however, could vary in different locations, time, and to different customers. The accurate determination might need an extensive study to find out the impact from the factors, such as energy price variation, load types, and customers' elasticity to energy prices etc. Due to the scope of this investigation, the determination of t_p is not deeply investigated. It is considered as an input into the charging scheme and chosen as the average of energy prices level in a day.

The charging and discharging cycles of the energy storage part controlled by customers in response to energy price are achieved through the following steps:

i) Determine charging/discharging durations that are driven by price variations throughout of the day. The time periods when energy prices are higher than the predefined price threshold t_p are treated as discharging candidates, and the periods when energy prices are lower than the threshold are regarded as charging candidates.

ii) Determine charging/discharging durations that are driven by the state of charge. The state of charge prior to the control strategies is assessed first. This will inform the amount of energy that the storage can absorb during charging period, and the amount of energy that the storage is capable of outputting during the discharging period. The duration for charging/discharging can then be calculated based on the charging/discharging current of storage battery and its voltage level.

iii) Determine the time to charge and the time to discharge based on the differences in charging/discharging durations derived from i) and ii). The determination should follow these two principles: 1) if the price driven charging/discharging duration is longer than the state of charge driven duration, the time to charge is the time that allows the state driven duration covers the periods with the lowest energy prices, whilst the time to discharge is the time that allows the state driven duration covers the periods with highest energy prices. 2) if the price driven charging/discharging duration is shorter than that of the state driven, the time to charge/discharge is the start of the price driven charging/discharging durations.

The process of charging and discharging cycles is graphically presented in Figure 4-5.

The remaining *(1-x)* of energy storage capacity conducted by network operators is expected to shave household peak demand to alleviate network congestion. The threshold in terms of demand t_d is determined as: if there is one congestion in a system, it is the maximum system demand, which causes network reinforcement either due to thermal violation or voltage violation, divided by total customer number and coincidence factor; otherwise, if there is no congestion in the system, it is set at an arbitrary level of 90% of original system peak divided by total customer number and coincidence factor.

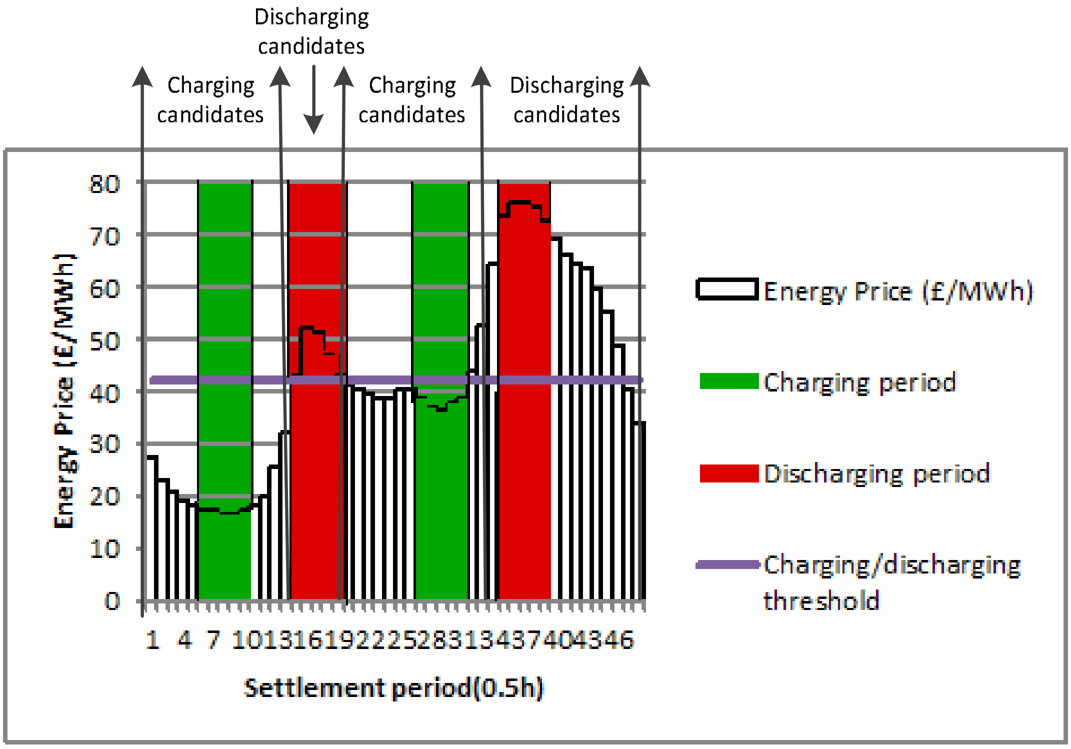


Figure 4-5 Charging/discharging period selection in response to energy price

The periods with demands lower than t_d are treated as charging candidate periods and the remaining period with demands higher than t_d are regarded as discharging candidate periods.

The energy storage part controlled by network operators is operated in the following steps:

i) Determine charging and discharging durations that are driven by network pressure points. For time periods when demands are higher than the predefined demand threshold t_d, they are treated as discharging durations, and the remaining periods are regarded as prospective charging durations.

ii) Determine the amount of energy that is required to discharge. This is determined by the amount of demand that exceeds the network capacity during the discharging period.

iii) Assess the state of charge and determine the charging duration. Based on the initial state of charge in the storage, the amount of additional energy required to charge in order to satisfy the discharge energy requirement will be obtained.

Thus, the duration of charging can be determined according to the voltage, the charging current of storage battery and the additional energy requirement.

iv) Determine the time to charge based on the calculated charging duration. In this process, the time to charge allows the battery to have sufficient time to charge additional energy from its initial state of charge, which will satisfy the discharge requirement.

The flowchart of the operation strategy for jointly owned energy storage is shown in Figure 4-6. It presents the charging/discharging cycle determinations based on response to energy prices and demand level. The new load profile $\boldsymbol{L}_{\text{new}}$ after applying energy storage is defined as a function $\boldsymbol{L_{new}(x)}$ with respect to x.

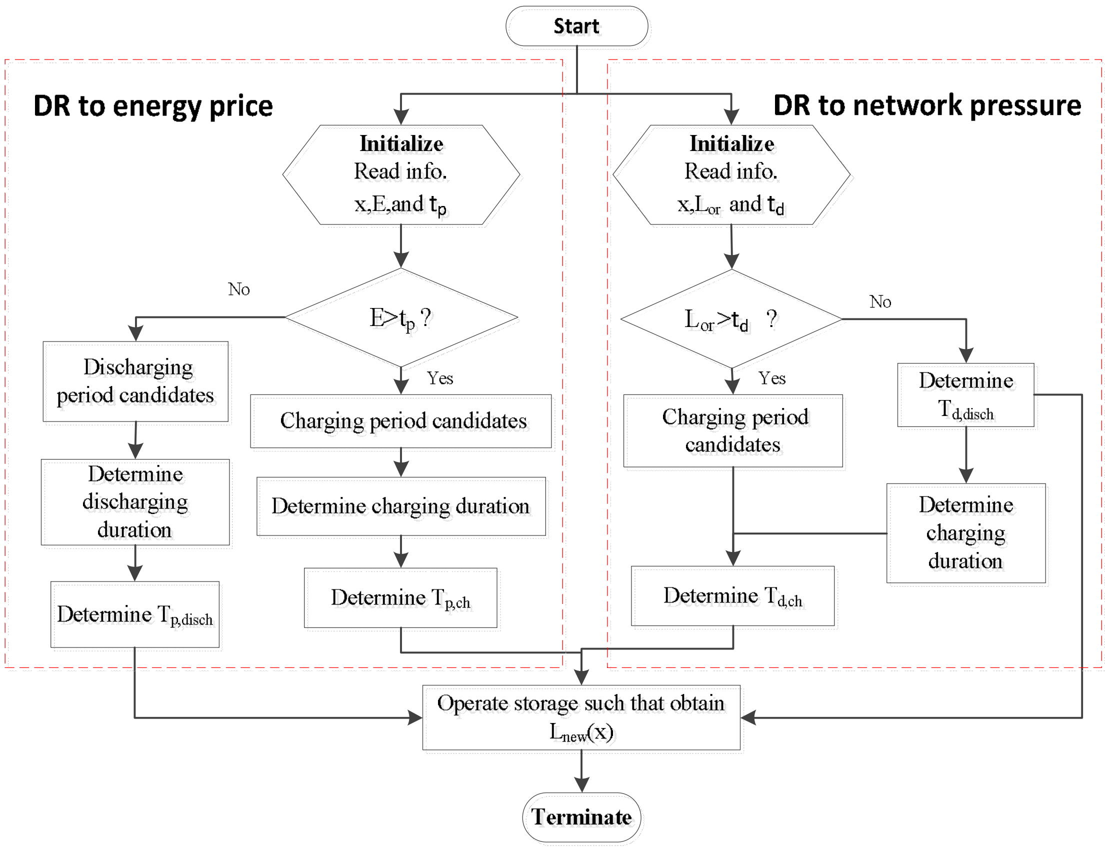


Figure 4-6 Flowchart of operation strategy of jointly owned storage

In order to define $\boldsymbol{L_{new}}(x)$, four 48×1 column vectors are firstly defined for the simplicity of explanation: $\boldsymbol{T}_{p,ch}$ and $\boldsymbol{T}_{d,ch}$, and $\boldsymbol{T}_{p,disch}$ and $\boldsymbol{T}_{d,disch}$. They represent: customer charging matrix, DNO charging matrix, customer discharging matrix and DNO discharging matrix respectively. The element in the four vectors is either 1 or 0.

In the first two vectors, 1 represents that the time slot is for charging while 0 is not. On the contrary in the second two vectors 1 represents that the time slot is for discharging while 0 is not. With the proposed operation scheme, the original household daily load profile is transformed to

$$\begin{aligned}\mathbf{L}_{new}(x) = \mathbf{L}_{or} &+ V_B \cdot I_{ch} \cdot x \cdot \mathbf{T}_{p,ch} \\ &- V_B \cdot I_{disch} \cdot x \cdot \mathbf{T}_{p,disch} + V_B \cdot I_{ch} \cdot (1-x) \cdot \mathbf{T}_{d,ch} \\ &- V_B \cdot I_{disch} \cdot (1-x) \cdot \mathbf{T}_{d,disch}\end{aligned} \tag{4-2}$$

where, V_B is storage battery voltage, I_{ch} and I_{disch} stand for charging and discharging current of a storage unit.

4.5 Yearly Energy Storage Dispatch Strategy

The previous section defines prefixed dispatch strategy of energy storage within a typical day, assuming the capacity share between customers and DNO is known and fixed. When this approach is applied to a whole year, the variable x is fixed for the whole period. This scheme is easy to implement but not flexible enough to respond to varying energy prices and network conditions. In order to improve the flexibility of storage operation, a dynamic yearly operation scheme is proposed. The main concept is that the operational capacity share between customers and network operators could vary from day to day. The target is to minimise total annual costs which are the sum of energy costs and network investment costs. The optimisation problem is formulated as:

1. Objective

$$\min \quad C_{dy,en} + C_{dy,ne} \tag{4-3}$$

where, $C_{dy,\ en}$ is the annual energy costs with dynamic operation, and $C_{dy,ne}$ is represented by present value of future investment under dynamic dispatch.

For annual benefit quantification, the time-varying energy prices are represented by the developed RTP tariffs in Chapter 3 as they are just designed to accurately reflect wholesale price variation. The RTP price variation over a day is denoted by a 1×48 row vector $\boldsymbol{E}$. The annual energy cost is a function of x, which can be obtained as the sum of the energy costs of all households served by a substation. Energy costs for a single household is the multiplication of the energy price, demand, and the duration.

$$C_{dy,en} = \sum_{i=1}^{365}\sum_{j=1}^{N} \mathbf{E}_{(i)} \cdot \mathbf{L}_{new,dy(i,j)}(x_i) \cdot t \cdot \alpha \tag{4-3.a}$$

where, i represents the number of day, and j is the number of households. $\boldsymbol{L}_{new,dy(i,j)}(x_i)$ is the load profile of the j^{th} household in the i^{th} day after the application of dynamic dispatch. t represents the length of each settlement period and α is the percentage of energy costs in electricity bills.

The network costs represented by present value of future investment can be expressed as a function of system peak demand

$$C_{dy,ne} = G(D) \tag{4-3.b}$$

where, D is the system peak demand and it is selected as the maximum value of everyday's peak demand , given as

$$D = \max\{\max(\sum_{j=1}^{N} \mathbf{L}_{new,dy(j)}(x_i))_i\} \tag{4-3.c}$$

2. Constraints

The constraints for the optimisation problem stem from physical structure of energy storage. As mentioned in Section 4.4.2, all the five scenarios are regarded as the candidates for daily energy storage share, in which x can be a discrete number. The candidate scenarios might or might not change over the time, depending on the variations in energy prices and network conditions. The constraints can be mathematically formulated as

$$x = \{0, 0.25, 0.5, 0.75, 1\} \tag{4-4}$$

This is a non-linear optimisation problem as the network investment is non-linear with respect to system peak demand. Due to that x can only be selected from a set of values, Enumeration approach [87] is adopted in programming to determine the optimal sets of values for x_1—x_{365}. Once the optimized x_i for each day is obtained, dynamic operation is realized.

4.6 Benefit Quantification of Household Energy Storage

This section introduces benefit quantification methods to measure the benefits that can be realised through applying the proposed operation schemes to energy storage. The benefits, in terms of savings in both network investment deferral and energy cost are considered.

4.6.1 Network Investment

Network reinforcement activities are defined by either thermal limit violation or voltage limit violation. Therefore, it is essential to determine how network reinforcement is driven by the two causes first.

1. Voltage violation driven investment

The per unit voltage drop along a feeder can be estimated with [88]

$$\Delta V \approx \frac{P \cdot R + Q \cdot X}{V} \tag{4-5}$$

$$V_{end} = V - \Delta V \approx V - \frac{S \cdot \cos\theta \cdot R + S \cdot \sin\theta \cdot X}{V}$$

where, P and Q are the per unit values of active power and reactive power along the feeder. V and V_{end} are the voltages at the beginning and end of the feeder. R and X are per unit values of the resistance and reactance of the feeder, and $cos\theta$ represents the power factor.

The acceptable voltage range is supposed to be from - 6% to +10% of the base value. If feeder end voltage is out of this range, the networks need to be reinforced, called voltage violation driven investment. In this study, voltage driven investment at substations is not considered.

2. Thermal violation driven investment

If the demand along a feeder is higher than its rating, it needs to be reinforced, defined as thermal violation driven. If the aggregated demand at a substation violates its capacity, investment on the substation is needed as well, which is also categorised as thermal violation driven investment.

In order to differentiate the investment driven by either thermal violation or voltage violation for a feeder, the following checking equation is formed

$$S_{\max\_v} = \frac{\left|\Delta V_{\max}\right| \cdot V \cdot S_{base}}{\cos\varphi \cdot R + \sin\varphi \cdot X} \tag{4-6}$$

where, ΔV_{max} is the maximum acceptable voltage drop along a feeder and S_{max_v} represents the maximum load that the feeder can support without voltage violation. S_{base} is the base power.

If S_{max_v} is larger than feeder's thermal rating, the reinforcement is thermal violation driven, otherwise it is voltage violation driven.

4.6.2 Benefit Quantification

The quantification algorithm devised here reflects the characteristics of LV networks through time and space.

1. Wholesale energy saving

The energy bills for customers are determined by their electricity use in each settlement period and the corresponding energy prices. The original annual energy costs for an examined network without energy storage are the summation of energy costs for each household over one year

$$C_{or} = \sum_{i=1}^{365}\sum_{j=1}^{N} \mathbf{E}_{(i)} \cdot \mathbf{L}_{or(i,j)}\, t \cdot \alpha \tag{4-7}$$

The new annual energy costs, C_{new} are the summation of energy costs for each household with energy storage over one year, evaluated in (4-3.a). If it is fixed operation scenario, the same equation is used but with a constant x through the whole year. The energy cost savings due to the operation of energy storage are the difference in annual energy costs before and after load shifting, defined as

$$\Delta C = C_{or} - C_{new} \tag{4-8}$$

Where C_{or} represents the original annual energy costs and C_{new} is the annual energy costs with applying energy storage.

2. Network investment deferral

Network investment deferral is determined by examining the changes in components' present value of future reinforcement [89]. The investment horizon of a feeder/transformer under a given load growth rate can be identified with

$$n = \frac{\log RC - \log D}{\log(1+r)} \tag{4-9}$$

where, RC is the feeder's/transformer's rating, r is load growth rate and D is system peak demand.

The change in its present value due to the peak shaving caused by energy storage is

$$\Delta PV = Asset\_Cost \cdot \left(\frac{1}{(1+d)^{n_{original}}} - \frac{1}{(1+d)^{n_{new}}} \right) \tag{4-10}$$

where, d is the discount rate, $n_{original}$ is the component's original reinforcement horizon and n_{new} is its new reinforcement horizon due to its flow reduction.

3. Total yearly benefits

The total benefits TB stemmed from the DSR enabled by household energy storage are the sum of savings from both wholesale energy costs and network investment costs.

$$TB = \Delta C + \Delta PV \cdot AnnuityFactor \tag{4-11}$$

4.7 Case Study

In this section, two distribution networks are used to testify the effectiveness of the designed prefixed and dynamic dispatch strategies, demonstrating the impacts on network conditions and quantifying the benefits of applying the jointly owned energy storage. The study is first conducted on a typical settlement day, which is then extended to a year.

4.7.1 Test Networks

In order to generalise the study, two types of practical radial LV networks with low and high utilisations are chosen, given in Figures 4-7 and 4-8 respectively [90].

The parameters of the two test networks, including feeder lengths and transformer capacities, are given in Table 4-2 and Table 4-3. Unit impedance of all feeders is chosen as 0.939+j0.076 (Ω/km). Power factor and predicted load growth rate together with coincidence factor, annuity factor and discount rated are chosen as 0.95, 2%, 0.8, 0.074 and 5.6% respectively [91]. Typical unit cost of feeders is 67,200 £/km and the unit cost of transformers is £26,400 [92].

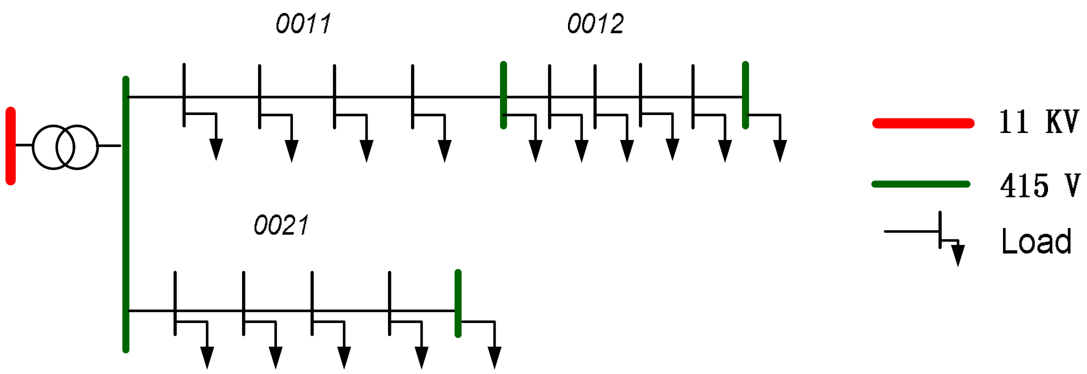


Figure 4-7 Layout of a radial LV network with low utilization in Illminster Avenue

Initial analysis found that in the lightly utilised network of Illminster Avenue, reinforcement will be driven by thermal limit violation of feeders, while the investment in Marwoord Road is largely caused by the thermal violation of the substation.

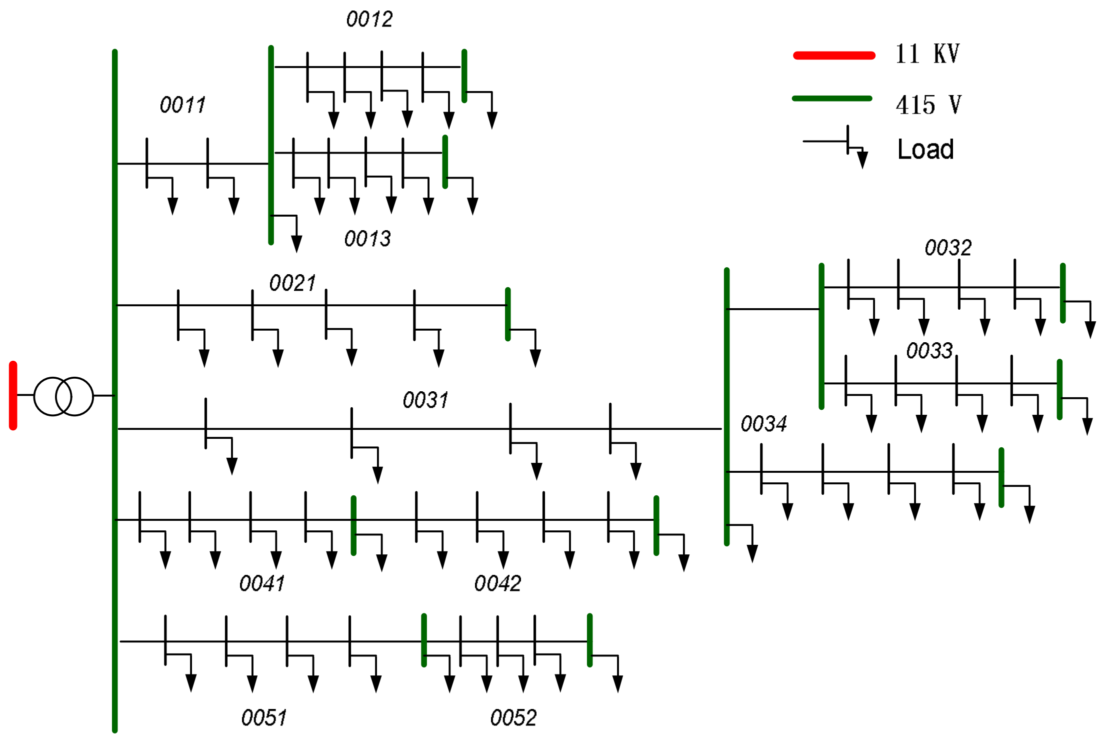


Figure 4-8 Layout of a radial LV network with high utilization in Marwoord Road

Table 4-2 Parameters of the two networks (A)

	Illminster Avenue	Marwoord Road
Transformer capacity (kVA)	750	500
Transformer utilization (%)	43.0	94.8
Feeder thermal rating(kVA)	204	204

4.7.2 Parameters of Energy Storage Battery

In this study, lithium-ion battery is chosen as example energy storage because of its advantages in the combination of performance capability, safety, life and costs over other types of batteries. The typical parameters of the storage battery are outlined in Table 4-4 [86].

Table 4-3 Parameters of the two networks (B)

	Feeder name	Number of customers per feeder	Feeder length(m)
Illminster Avenue	Feeder 0011	118	295
	Feeder 0012	18	88
	Feeder 0021	121	287
Marwoord Road	Feeder 0011	3	172
	Feeder 0012	13	109
	Feeder 0013	12	110
	Feeder 0021	67	268
	Feeder 0031	6	170
	Feeder 0032	29	301
	Feeder 0033	42	191
	Feeder 0034	10	101
	Feeder 0041	14	120
	Feeder 0042	52	233
	Feeder 0051	125	345
	Feeder 0052	4	0

Table 4-4 Parameters of Lithium-ion storage battery

	Unit
Battery capacity	2.4kWh
Depth of discharge limited	2kWh(80% depth of discharge)
Battery charging current limit	<20% of rated AmpHours
Battery discharging current limit	<20% of rated AmpHours

4.7.3 Daily Result Demonstration

For the purpose of simplicity, two assumptions are made: i) the daily energy price variations that all customers see in the two networks are the same, which could be either conforming or conflicting with demand changes (in Figure 4-1); ii) the unit aggregated load profiles in the two systems are supposed to be identical as well (in Figure 4-4). The benefits of energy storage, in terms of daily energy cost saving and household peak reduction, are quantified under Scenario 1 (100% by customers) and Scenario 3 (50% by customers and 50% by DNOs). Savings in network investment are quantified in the next section.

With conforming prices, the unit aggregated demand profiles at load points with and without energy storage are illustrated in Figure 4-9. The original load profile is very steep and has two obvious spikes. Due to demand shifting with energy storage, new demand profiles in Scenarios 1 and 3 have quite different shapes, which are relatively flatten. As noticed, the daily household peak demand is reduced from 1.90kW to 1.74kW in Scenario 1 (benchmarking scenario) and by contrast, the peak is further reduced by 0.16kW in Scenario 3 on the basis of Scenario 1. The daily wholesale energy cost of an individual household decreases from £1.378 to £1.325 in Scenario 3. Generally, the introduction of shared energy storage generates 3.85% energy cost reduction and 16.99% peak demand reduction.

The unit demand profiles at load points in conflicting price case are depicted in Figure 4-10. The peak demand per household is reduced from 1.90 kW to 1.74 kW in Scenario 3; on the contrary, the household peak increases to 2.01 kW in Scenario 1. The daily energy cost of an individual household decreases from £1.247 to £1.145 in Scenario 3, achieving 8.18% reduction. DSR facilitated by storage results in both peak and trough demand increase in Scenario 1, but it can reduce household peak by approximately 8.25% and smooth load profile in Scenario 3.

The quantified daily benefits in both conforming and conflicting price cases are summarised in Table 4-5. For household peak demand reduction, both Scenario 1 and 3 will lead to positive values under conforming prices. In Scenario 1 with conflicting prices, however, the household peak is reduced by around -8%, i.e. there is 8% increase. This is due to the coincidence of trough price and peak demand in conflicting price case. Energy cost savings in Scenario 3 are always less than those in Scenario 1 as there is less proportion of energy storage controlled by customers.

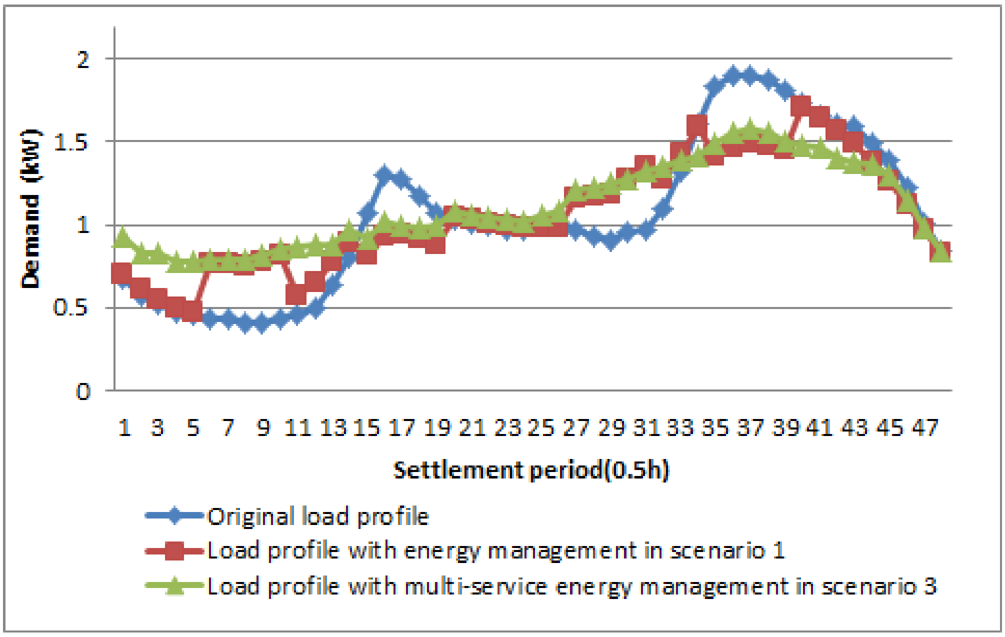


Figure 4-9 Unit aggregated demand profiles at load points under conforming price

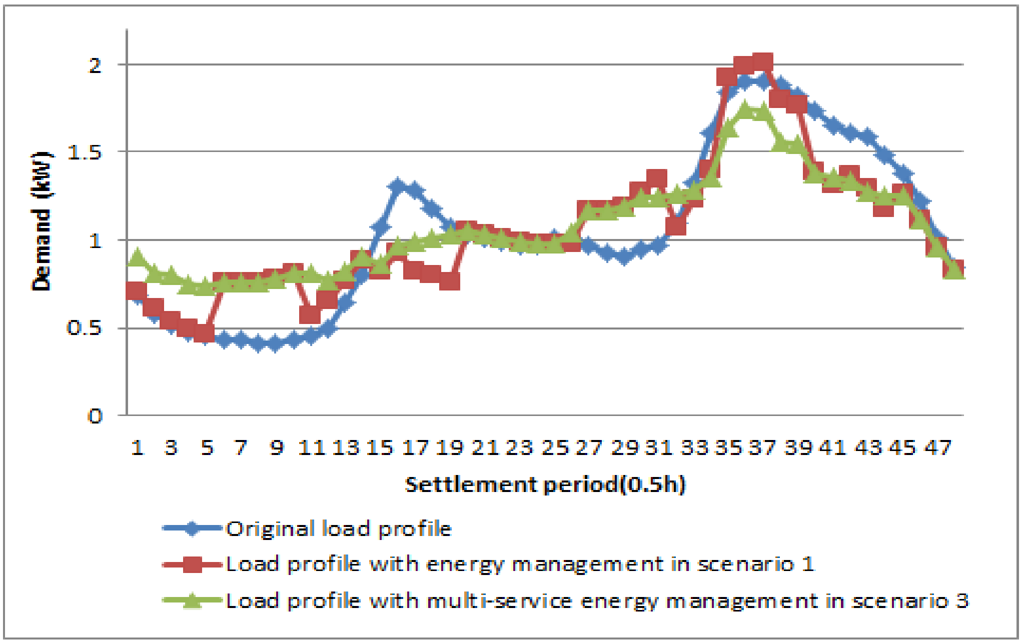


Figure 4-10 Unit aggregated demand profiles at load points under conflicting price

Table 4-5 Summary of daily benefits for a typical household

Control scenario	Price case	Energy cost saving (%)	Peak demand reduction (%)
Scenario 1 (benchmarking)	Conforming price	5.88	12.72
	Conflicting price	10.26	-7.89
Scenario 3	Conforming price	3.85	16.99
	Conflicting price	8.18	8.25

4.7.4 Annual Benefit Quantification

Annual wholesale cost savings and network investment saving stemmed from DSR facilitated by energy storage are quantified in two cases:

i) Case one: the energy storage capacity share is prefixed throughout the whole year, defined as prefixed case;

ii) Case two: the storage capacity share varies from day to day, regarded as dynamic case.

The RTP tariffs over a year used to trigger DSR on behalf of energy prices are shown in Figures 3-7 and 3-8. The predicted annual demand information is from [93]. The variation tendency of demand over a year is shown in Appendix B.3.

1. Prefixed dispatch

In the prefixed case, Scenarios 1- 5 are deployed separately to quantify the benefits and find how differing shared ownerships affect annual benefits, listed in Table 4-6. Operation of energy storage in Scenario 1 merely responds to energy prices, which is conventional operation scheme. It is chosen as benchmarking scenario to compare the benefits from other scenarios. From Table 4-6, benchmarking Scenario (Scenario 1) brings about the total benefit of £7,089 annually for the highly utilised network in Marwoord Road. With increasing storage capacity controlled by DNOs, both network savings and total benefits grow. Particularly, when the prefixed dispatch is under Scenario 5, the total benefit can rise up to £8,093. The additional saving of £1,004 is entirely from network investment because the wholesale energy saving in Scenario 5 is £954 less than that in benchmarking Scenario.

Table 4-6 Annual energy cost and network investment cost savings

Prefixed dispatch(£/year)			Marwoord Road	Illminster Avenue
Scenario 1	Wholesale energy saving		4765	740
	Network saving	Transformer	891	189
		Feeder	1433	273
	Total benefit		7089	1202
Scenario 2	Wholesale energy saving		4,733 (-32)	735 (-5)
	Network saving	Transformer	936 (+45)	189 (0)
		Feeder	1,506 (+73)	277 (+4)
	Total benefit		7,175 (+86)	1,201 (-1)
Scenario 3	Wholesale energy saving		4,687 (-78)	724 (-16)
	Network saving	Transformer	1,000 (+109)	190 (+1)
		Feeder	1,628 (+195)	282 (+9)
	Total benefit		7,316 (+227)	1197 (-5)
Scenario 4	Wholesale energy saving		4,352 (-413)	656 (-84)
	Network saving	Transformer	1,243 (+352)	191 (+2)
		Feeder	2,208 (+775)	308 (+35)
	Total benefit		7,803 (+714)	1155 (-47)
Scenario 5	Wholesale energy saving		3,811 (-954)	549 (-191)
	Network saving	Transformer	1,594 (+703)	194 (+5)
		Feeder	2,688 (+1255)	348 (+75)
	Total benefit		8,093 (+1004)	1,092 (-110)

**Note: the values in parentheses are the additional benefits compared with those in benchmarking scenario (Scenario 1).

On the other hand, the savings from network investment vary with different scenarios and network utilization levels. In the highly utilised network of Marwoord Road, up to £1,004 per year in network investment saving is achieved, but it is less than £80 for the lightly utilised network in Illminster Avenue whatever the scenario is. For Illminster Avenue network, the benchmarking scenario produces larger total benefits of £1,202 annually, compared with other scenarios whose annual total benefits range from £1,092 to £1,201. The results explain that the application of jointly owned storage in Illminster Avenue is less efficient in producing benefits.

Above results prove that compared with conventional energy storage operation schemes, which only respond to energy prices, the operation based joint ownership can produce more benefits, particularly much more total cost savings for highly utilised networks. Therefore, in order to gain more benefits under prefixed dispatch cases: i) for low utilised networks, more proportion of energy storage capacity should be allocated to respond to energy prices; and ii) for highly utilised networks, more storage capacity should be arranged to respond to network conditions.

2. Dynamic dispatch

Dynamic dispatch is demonstrated to further explore benefits from using multi-service energy storage. By employing the scheme proposed in Section 4.5, the optimal dispatch scenario for each day in a settlement year can be identified. The probability density of household storage ownership through the year is shown in Figure 4-11. It can be seen that nearly 50% of the days fall into Scenario 1 and less than 20% days select Scenarios 4 and 5. It means that the majority of DSR facilitated by energy storage is expected to respond to energy price variation.

With the application of energy storage for one year, the quantified annual benefits are provided in Table 4-7. On the whole, dynamic operation generates the total annual benefits of £9,026 for the highly utilised network and £1,276 for the lightly utilised system. There are extra benefits of £1,937 and £74 respectively compared with the benchmarking scenarios. In addition, the total benefits obtained with the dynamic operation are larger than those from other prefixed dispatch scenarios for both networks. This is due to that cost savings from network investment deferral in dynamic operation are the same as those in prefixed Scenario 5, while the wholesale energy savings are close to the values in prefixed Scenario 1.

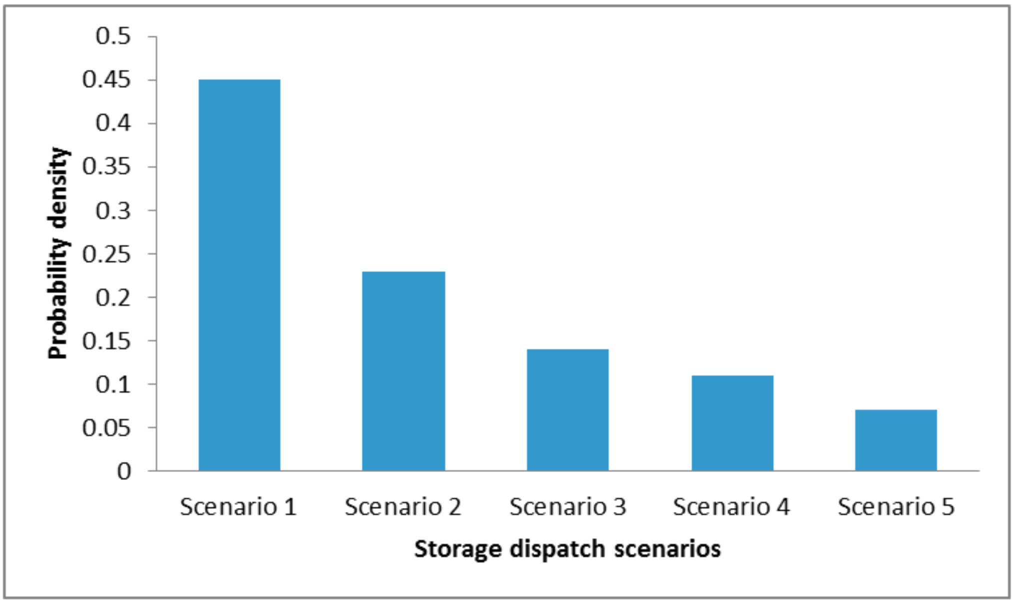


Figure 4-11 Probability density of storage ownership dispatch in a year

The results in Table 4-7 indicate that dynamic operation can bring more benefits than conventional and prefixed operations under both highly and lightly utilised networks. To be specific, dynamic operation can produce not only huge network investment savings but also plenty of wholesale energy cost savings. Therefore, it is the most effective approach for controlling energy storage to facilitate domestic DSR.

Table 4-7 Annual cost savings with dynamic dispatch

			Marwoord Road	Illminster Avenue
Dynamic dispatch (£/year)	Wholesale energy saving		4,744 (-21)	734 (-6)
	Network saving	Transformer	1,594 (+703)	194 (+5)
		Feeder	2,688 (+1255)	348 (+75)
	Total benefit		9,026 (+1937)	1,276 (+74)

4.8 Chapter Summary

This chapter proposes a new method to enable DSR by shared battery and smart variable tariffs with RTP patterns. A innovate dispatch strategy is developed for shared ownership of domestic storage battery utilization between customers and DNOs. The aim is to facilitate domestic DSR to effectively respond to pressures in energy prices and distribution network conditions. Compared with the status quo position where domestic energy storage is entirely owned by households and operated only to reduce energy cost, the joint ownership offers additional flexibility to meet customers and network operators' needs. It, thus, can maximise the value from installing domestic storage and encourage more uptakes of domestic storage.

Chapter 5

Enhanced Battery Management for Demand Response

THIS chapter proposes an innovative method to improve the battery share between customers and network operators. It aims to enable high density PV to connect to LV distribution networks efficiently.

5.1 Introduction

Chapter 4 has introduced an effective DSR approach enabled by energy storage with shared ownership for both energy cost saving and network investment saving. However, the drawbacks of this method are as follows:

i) For each settlement day, a specific scenario of storage dispatch is selected to respond to price pressure and network pressure. However, the degrees of these pressures vary dramatically from a settlement period to another. Therefore, this method, which maintains the battery dispatch scenario unchanged within a day, is unable to vary the storage capacity operated by customers or DNOs effectively along with price or network condition.

ii) The DSR using shared energy storage focuses on the management of energy from conventional main grid. Its correlation with DG is not considered.

In order to address these two issues, solutions are proposed as:

i) Explore a new approach by which the percentage of storage capacity operated by customer/system operator is able to change within a day for optimal dispatch of energy storage.

ii) Improve the operation of storage battery for efficient use of distributed renewable generation.

Therefore, this chapter proposes an innovative methodology to enable high density PV solar generation to connect to LV distribution networks more efficiently through using in-home battery and smart tariffs for domestic customers. The methodology employs “shared” battery, responding to smart variable tariffs and network pressures through a new approach defined as “charging envelope”, to achieve the dual goals of minimizing energy costs and mitigating network constraints. The effectiveness of the proposed methodology is demonstrated on a practical LV network with substantial in-home distributed generation and storage battery. Furthermore, for customers’ better understanding of the benefit from energy management coordinated with PV and energy storage, the whole-system financial saving can be converted into per unit cost reduction in electricity bill.

5.2 Problem and Proposed Solution Statement

The penetration level of distributed PV solar generation in LV network is growing rapidly across GB [94-96]. If PV arrays are integrated into household EMS, the energy generated from sun light irradiation can be used as a supplement of conventional generation to support local demand and reduce energy import from the power grid. For a dwelling equipped with PV, distributed energy storage battery can also be installed in order to improve demand flexibility. In the distributed EMS system, the PV is directly linked to the distributed battery by using direct current (DC) connection. The alternating current (AC) lighting circuits can also be converted to DC to enable light-emitting diode (LED) lighting and other DC appliances.

During daylight time, the output of a PV array is entirely dependent on real-time solar irradiance and it can directly supply the DC load. Excessive energy can be stored in battery storage for late use, or the DC power can be transformed into AC power by invertor so that it can be exported to the public distribution network. On the contrary, when PV output is not sufficient to supply local DC load, customers can use the energy released from the battery to run small DC appliances. Therefore, in order to utilize the generation from PV effectively and solve key network problems which arise with PV integration, the operation of in-home storage battery with financial incentives and technical solutions is of significant importance. Battery control algorithm needs to be designed for reducing total energy consumption, shifting peak demand, and eventually increasing financial benefits for end customers.

The schemes for managing energy storage have received extensive attention in the literature. The most conventional way to control energy storage is based on variable energy prices to conduct charging/discharging during off-peak/peak price periods [77, 97]. Besides, references [98, 99] aimed to compute an optimal size for storage instead of developing a novel scheme on a fixed storage unit for energy management, and reference [100, 101] paid more attention to evaluate the benefit in terms of financial saving brought by operating energy storages in distribution systems. The main target of these investigations is to minimise energy cost, but network investment in not taken into consideration.

Other storage management approaches with the consideration of network have also been proposed. References [102, 103] focused on the impact of energy storage in power flow management and voltage control, and reference [104] presented an optimal storage operation strategy to flatten load profiles and reduce peak demand. However, they do not closely link the network pressure to energy pressure. Meanwhile, the investigations based on a typical day are not extended to a whole year.

Reference [105] presented a heuristic algorithm to optimise the revenue generated by an energy storage unit which is connected with a large capacity of DG. This work focused on a single DG and a storage unit instead of the flexible interaction among a number of small devices at household level. Reference [106, 107] employed shared energy storage to respond to both energy price and network condition for energy cost reduction and network investment deferral, but the cooperation with DG and DC load is still ignored.

Therefore, this chapter proposes a novel approach to manage energy storage in response to both energy pressure and network pressure when large-scale DG is connected to LV systems. Instead of relying on dynamic prices to reflect network congestion, a new concept of “charging envelope” is introduced to provide DNO with greater certainty in mitigating network pressure. With the aid of the proposed charging envelopes, DNOs will reserve a proportion of battery capacity during the anticipated congested periods to support the network operator and mitigate network pressure. The shape of the charging envelop designed for network operation is therefore closely linked to network constraints. Within the restriction of the charging envelop, storage can be operated to minimise energy costs in response to smart variable tariffs.

In this study, the smart variable tariffs are not only capable of reflecting energy price variation, but also motivating cost savings in energy generation and supply. These tariffs will be trialled on the domestic installations to incentivise customers to alter their demand profile, flattening their demand, reducing their peaks using the PV and battery storage.

Even though variable tariffs are usually effective for DSRs, general public are unwilling to accept them due to complex methods of settlement. Therefore, the smart variable tariffs are used to trigger DSR of the storage battery rather than charging customers in this study. A new form of smart tariff, defined as smart fixed tariff, is proposed as the actual tariff employed for charging end users. By converting the whole-system benefit to tariff rate discount, the smart fixed tariff is not only easier for customers to understand, but also guarantees returns for the participants in energy management in a simple way.

The contribution of this chapter lies in:

i) it proposes a new way to enable battery share for energy management improvement;

ii) it introduces the concept of charging envelope to reserve battery capacity for network pressure mitigation and distributed generation usage;

iii) it proposes an innovative battery charging strategy through using charging envelopes and smart variable tariffs;

iv) it quantifies the benefits in terms of energy cost saving and peak demand shaving from integrated EMS;

v) it proposes an innovative smart fixed tariff to reward customers for their participation in energy management.

The rest of the chapter is organized as follows: Section 5.3 details the rationale of charging envelope design. Section 5.4 presents the design process of charging envelopes if there is no congestion in distribution networks. Section 5.5 describes the improvement of the charging envelopes in order to mitigate network pressure when congestions occur. The battery charging algorithm under charging envelope is proposed in Section 5.6, and the whole-system benefit from charging envelope application is evaluated in Section 5.7. After a numerical case study in Section 5.8, conclusions are drawn in Section 5.9.

5.3 Rationale of Designing Charging Envelope

The charging envelopes are actually boundaries that define and constrain the state of charge (SoC) of battery, including start time, duration and slopes of charging/discharging. The upper and lower boundaries of charging envelopes constrain the maximum and minimum battery SoCs. In the operation process, the battery will charge and discharge between the upper and lower boundaries dictated by charging envelopes. Figure 5-1 demonstrates the concept of charging envelope for battery management.

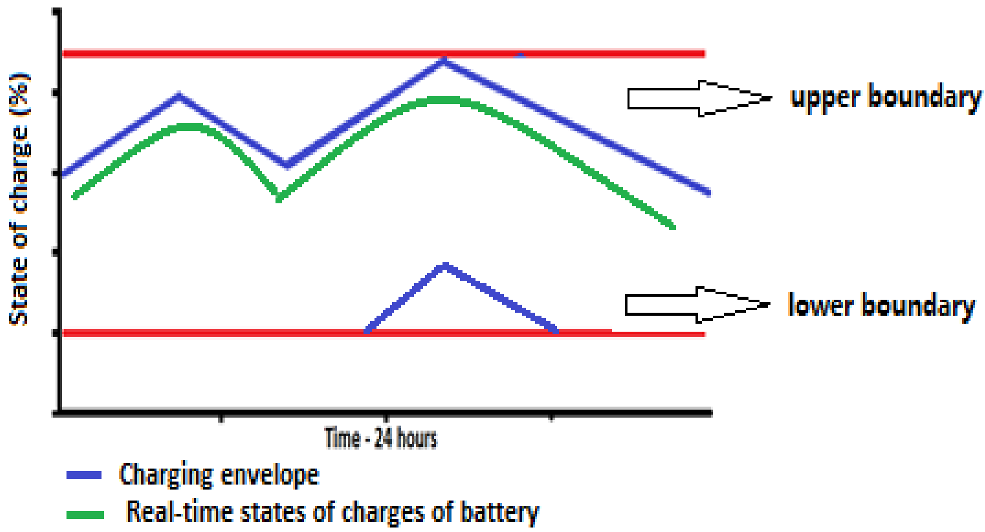


Figure 5-1 Relationship between charging envelope and real-time battery SoC

Battery charging envelopes constrain the amount of battery capacity reserved for resolving network constraints and supplying DC load during discharging periods, and the capacity reserved for accommodating PV charging and grid charging when energy price is low. As illustrated in Figure 5-1, the increasing (charging) slope of the upper boundary in a charging envelope constrains battery SoC change along with time. It is determined by the potential energy absorbed from PV and grid in order to make maximum use of distributed generation and cheap energy. By contrast, the decreasing (discharging) slope of the upper boundary intends to push SoC to decrease in order to release sufficient energy for mitigating network pressure. The difference between peak and trough points of a decreasing slop refers to the discharged energy for assisting network operation. Similar to the upper boundary, the increasing slope of the lower boundary define the minimum charged energy required for resolving network pressure. The decreasing slope is used to determine the potential energy released from battery to meet local demand. The SoC of the battery should be within the upper and lower boundaries so that it can be maximally utilised to mitigate energy price and network pressures.

Typically, networks have two operation conditions: without congestion usually during light-load periods and with congestion typically high-demand periods, thus charging envelopes are designed specifically for the two different cases.

The design of charging envelops for uncongested networks has the following steps:

i) identify the amount of energy that can be absorbed from PV generation and released to support DC load.

ii) use the identified information to determine upper boundaries.

iii) conduct battery charging/discharging behaviours within the upper and lower boundaries of charging envelopes to respond to smart variable tariffs.

In contrast, the design of charging envelops for congested networks has the following steps:

i) identify the degree and duration of network congestion, either driven by thermal limit violation or by voltage limit violation.

ii) use identified information to determine the energy needs to be charged/discharged during the congested periods.

iii) use calculated charging/discharging energy amount to determine increasing/decreasing slopes in upper and lower boundaries design.

iv) modify charging envelopes under different network constrains to accommodate varying degree and duration of network pressure.

v) conduct battery charging/discharging behaviours within the upper and lower boundaries of charging envelopes to respond to smart variable tariffs.

5.4 Charging Envelope without Network Congestion

This section basically introduces battery charging envelope design for network without congestion. Generally, it consists of three parts: Section 5.4.1 specifics battery charging/discharging path that is capable of changing battery SoC. Section 5.4.2 identifies the load and PV generation profiles for the demonstration of the proposed method, and the detailed process of charging envelope design is described in Section 5.4.3.

5.4.1 Charging/Discharging Path Specification

Since charging envelope is designed to manage the SoC of storage battery, all possible cases that would lead to SoC change needs to be considered. This part aims to clarify battery charging and discharging paths and determine energy flow directions of storage batteries. They will be fed into charging envelope design for different time intervals.

Battery charging paths can be initialised in three forms, depending on PV generation amount.

- The first form is defined as PV charging path, indicating that the energy supplied to battery is from solar irradiation. In this scenario, local DC load is also supported by PV generation. If there is still extra energy from PV, it can be exported to the main grid.

- The second charging path enables battery to withdraw energy totally from the main grid when there is not enough generation from PV. It is defined as grid charging path and in this case, the energy for DC load is from the main grid as well.

- The third charging path is defined as hybrid charging path. The available output from PV is absorbed by the battery and DC load. Any shortfall of battery charging is from main grid.

All the three charging paths are illustrated in Figure 5-2. In graphs (a)—(c), the solid arrows represent the actual power flow direction, and the dash arrow stands for the direction of power flow that might appear.

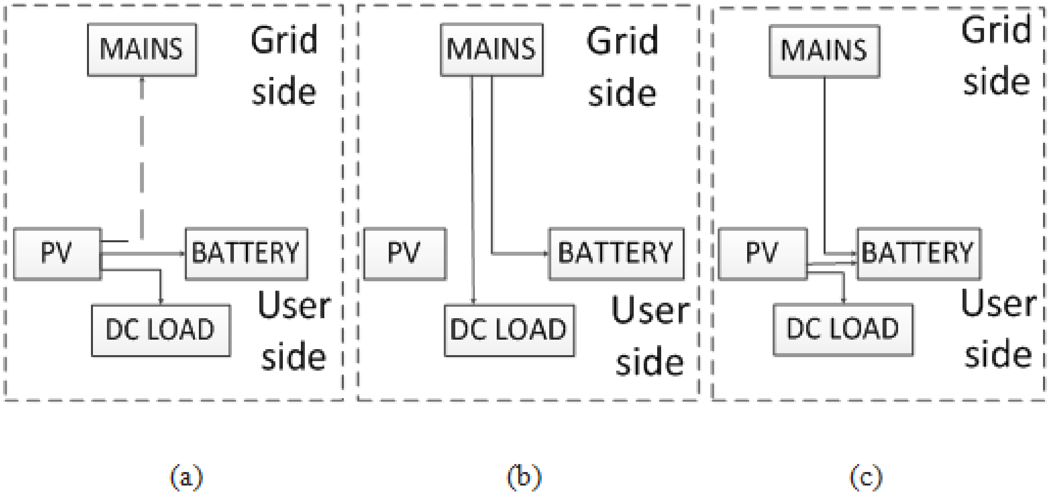


Figure 5-2 (a) The first charging path (PV charging path) (b) The second charging path (grid charging path) (c) The third charging path (hybrid charging path)

In contrast with charging paths, two battery discharging paths are identified in the following. The first discharging path defined as unidirectional discharging path assists battery to supply power to DC load. While, the second discharging path can not only allow DC load to draw energy from the battery, but also convert stored energy to AC and export it to main grid. This discharging path is therefore defined as bidirectional discharging path. The two discharging paths are shown in Figure 5-3.

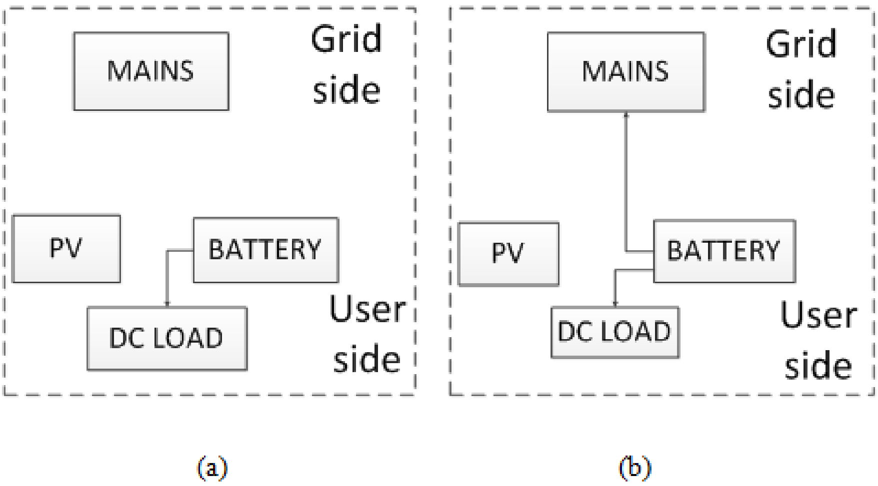


Figure 5-3 (a) The first discharging path (unidirectional discharging path) (b) The second discharging path (bidirectional discharging path)

5.4.2 Load and Generation Profiles Identification

The load profiles and PV generation levels vary dramatically over a year due to the changing energy consumptions and weather conditions. They may lead to different shapes of charging envelopes to manage battery SoC. For a typical domestic household in GB, the typical examples of daily load profiles [29] and PV outputs [108] for four seasons are plotted in Figures 5-4, 5-5 and 5-6. The data is collected every half-hour and 48 settlement periods are divided within a settlement day. In addition, the daily DC load profile for a typical household is assumed unchanged over a year, illustrated in Figure 5-7 [109].

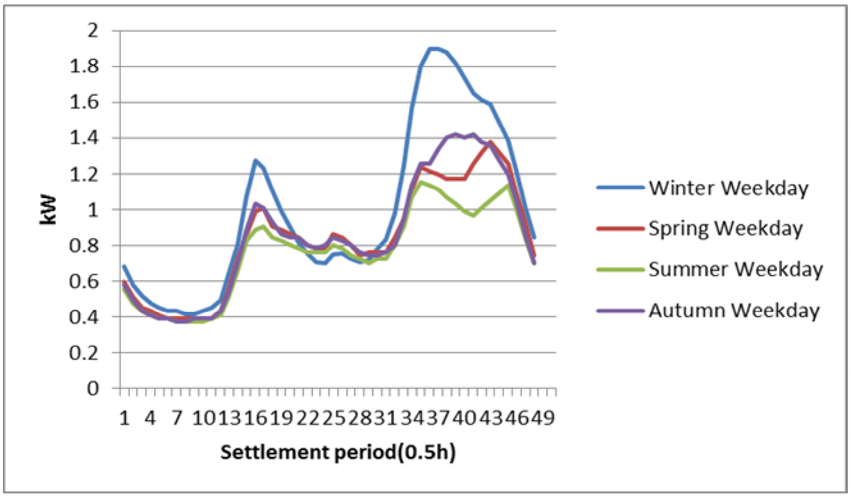


Figure 5-4 Typical AC load profiles for a household at weekdays

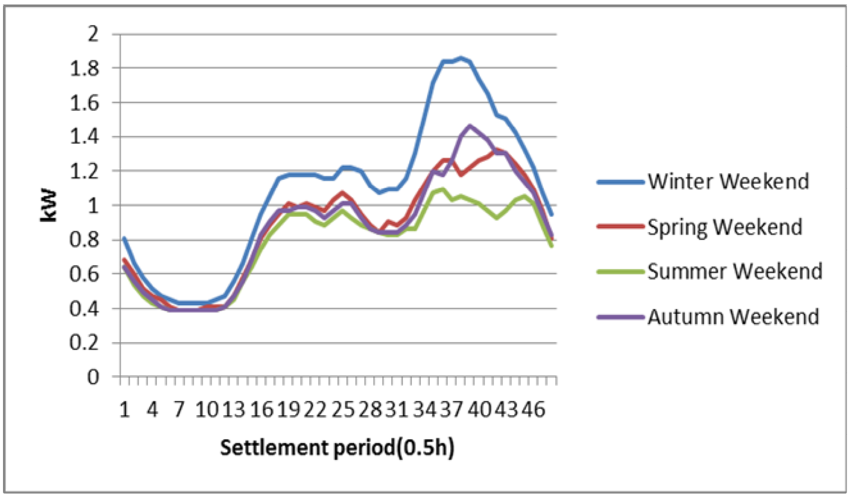


Figure 5-5 Typical AC load profiles for a household at weekends

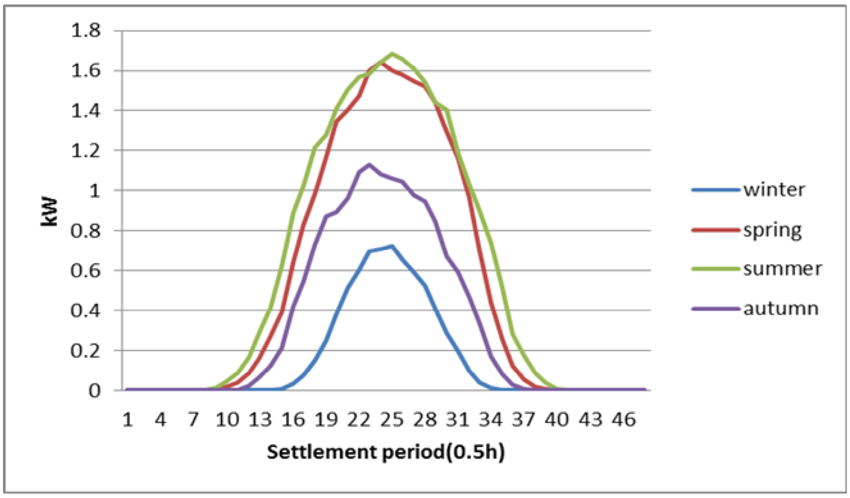


Figure 5-6 Generic household PV generation profiles

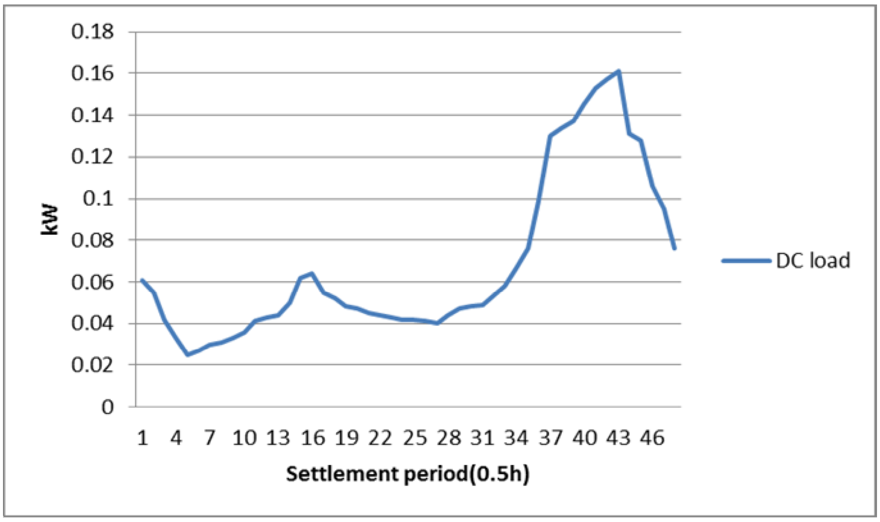


Figure 5-7 Typical household DC load profile

For both weekdays and weekends, the conventional AC load levels in winter are higher than those in other seasons and their peak demands normally occur in early evenings. However, the winter PV generation amount is the lowest, only one fifth of that in summer. On the contrary, there are flatter load profiles with large PV outputs in typical summer days. The peak loads and PV generations in spring and autumn are between those in winter and summer. The charging envelope designs for different day types (weekdays and weekends of four seasons) are based on the typical load and PV information presented here.

5.4.3 Charging Envelope Determination

Considering the efficiency of battery charging, SoC is expected to stay in the region from 20% to 90% of battery capacity. The SoC region from 90% to 100% is excluded for energy management due to low charging power as shown in Figure 5-8. Besides, if a Lithium-ion battery is fully charged, it will be stressed by high voltage. As a result, the Lithium-ion battery may suffer from capacity loss, meaning that it won't be able to hold as much energy as originally expected [110]. The SoC from 0% to 20% is not included as well because deep discharging may damage storage or reduce its lifetime [111, 112]. Therefore, 90% and 20% are set as upper and lower limits of battery SoC respectively.

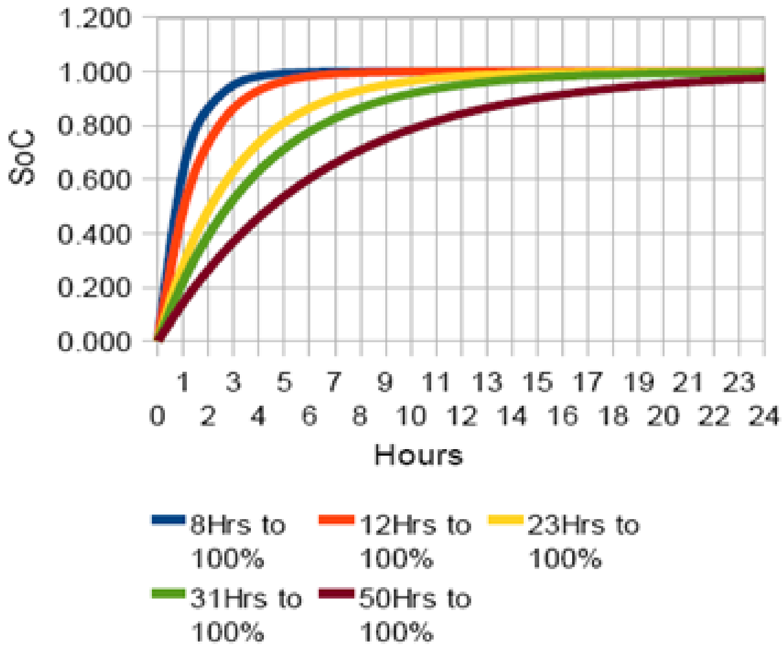


Figure 5-8 Typical battery charging profiles [109]

This section designs charging envelopes assuming that there is no network congestion in LV networks. As there is no specific requirement for battery charging/discharging to support network, it can be mainly used to store energy from PV, and to shift energy consumption for lower costs. Accordingly, the charging envelope design follows:

1. Rough differentiation of charging/discharging period

Before designing charging envelope for a typical day, the charging or discharging behaviour during a specific period need to be determined firstly. As shown in Figure 5-9, a settlement day can be roughly divided into four periods, defined as: overnight charging period (Period 1), morning discharging period (Period 2), day-time charging period (Period 3) and evening discharging period (Period 4) respectively. The reason for this differentiation is to respect the characteristics of PV generation and load profiles. Since the majority of PV generation locates in daytime and therefore charging is strongly encouraged in Period 3. In contrast, there is little PV generation in Period 4 and peak demand always occurs in this time interval, so SoC is encouraged to decrease in this period. Period 1 supplies a time slot to charge battery in response to off-peak prices and Period 2 can provide a period to discharge part of stored energy and preparing better charging in Period 3. Due to different load profiles and PV generation throughout seasons, a generic charging envelope is developed for each day type.

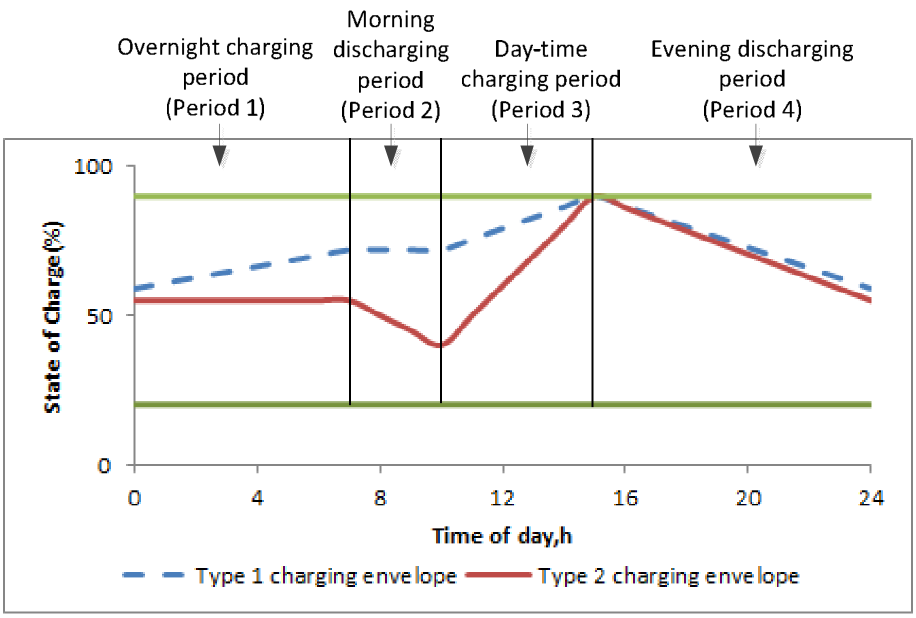


Figure 5-9 Rough deviation for charging/discharging period

2. Day-time charging slope and duration

As the promotion of DG is the key drive for charging envelope design, the charging slope and duration in Period 3 is determined firstly. As PV generation is expected to be used sufficiently, it can be set that the shortest period with no less than 80% of daily PV output is defined as Period 3.

The battery capacity reserved for day-time charging represents that a certain amount of energy is mainly absorbed from PV. Due to the uncertainty of the PV generation, the daily generation amount in a household over a season follows normal distribution, denoted by

$$G \sim N(\mu, \delta^2) \tag{5-1}$$

where, μ is the average household PV output and δ stands for the standard deviation.

If the confidence level is selected as $1\text{-}\alpha$, the confidence interval for μ [113] is

$$(\overline{X} \pm \frac{S}{\sqrt{n}} t_{\alpha/2}(n-1)) \tag{5-2}$$

where, n is the number of generation samples in different days. X and S represent the average PV generation and standard deviation.

The minimum daily PV output can be derived by

$$G_{\min} = \overline{X} - \frac{S}{\sqrt{n}} t_{\alpha/2}(n-1) \tag{5-3}$$

Therefore, the SoC of battery is constrained to have a minimum increment of G_{min} during the day-time charging period. In charging envelope design, it is equal to the reserved capacity C_{da_ch}, reflected as the increase level of SoC in the upper boundary. At the end of Period 3, the upper boundary is expected to reach the upper limit of battery, which has been set as 90% of SoC in this study.

3. Evening discharging slope and duration

The domestic load levels in the evenings are generally the highest within a settlement day and discharging is encouraged to provide energy to DC load and avoid peak increment.

The evening discharging period starts from the end time point of the day-time charging period (Period 3). The battery can supply DC load until the settlement period, whose demand is lower than average daily demand. The duration of evening discharging period is defined as T_{ev}, and the discharging slope is determined according to DC load level. Thus, the capacity reserved for this discharging period is

$$C_{ev\_dis} = L_{DC,ev} \cdot T_{ev} \tag{5-4}$$

where, C_{ev_dis} represents the reserved battery capacity for evening discharging. $L_{DC,ev}$ is the maximum DC load levels in the period. The amount of the reserved capacity for discharging to DC load is reflected as SoC decrement in the upper boundary during Period 4.

4. Overnight charging slope and duration

The required charging/discharging energy during Period 1 and 2 is quantified as the difference between the SoC in the upper boundary at the beginning of Period 3 and that at the end of Period 4. If the SoC at the end of Period 4 is lower than that in the beginning of Period 3, battery need to be charged in Period 1. The reason of charging battery from conventional power supply sources mainly lies in low energy price during this period. In this case, the shape of the charging envelope is Type 1 shown in Figure 5-9. Otherwise, battery charging is not encouraged during this time interval and the upper boundary is flat, defines as Type 2. This potential morning charging starts from the end of Period 4 until the settlement period whose demand is higher than the average daily demand. In this step, the reserved charging capacity is

$$C_{ov\_ch} = \begin{cases} S_{da,be} - S_{ev,en} & if\ S_{da,be} > S_{ev,en} \\ 0 & Otherwise \end{cases} \tag{5-5}$$

where, C_{ov_ch} represents the reserved capacity for overnight charging. $S_{da,be}$ and $S_{ev,en}$ denote the SoC in the upper boundary at the beginning of day-time charging period (Period 3) and that at the end of evening discharging period (Period 4). The reserved capacity for overnight charging is also reflected as SoC increment in upper boundary during Period 1.

5. Morning discharging slope and duration

Between Period 1 and Period 3, there is another period in which battery can release energy to support local load. From the end of overnight charging period (Period 1) to the start of day-time charging (Period 3), the discharged energy amount is

$$C_{mo\_dis} = \begin{cases} S_{ev,en} - S_{da,be} & if\ S_{da,be} < S_{ev,en} \\ 0 & Otherwise \end{cases} \tag{5-6}$$

where, C_{mo_dis} represents the reserved battery capacity for discharging in the morning. Similarly, the SoC upper boundary change over Period 2 presents the reserved capacity for morning discharging.

5.5 Charging Envelope with Network Congestion

If network congestions occur in a distribution system, the charging envelopes need to be modified to accommodate the congestion conditions. Generally, network congestions can be caused by either thermal limit violation or voltage limit violation. Therefore, charging envelopes should be designed purposefully to tackle different network congestions. This section mainly investigates charging envelop development to relieve network congestions driven by overloading and over generation in a LV distribution system.

5.5.1 Network Congestion Driven by Overloading

In networks with high-level overloading stresses, more energy from battery storage is required to meet local demand. Thus steeper discharging slopes are needed, which are normally associated with the upper envelop boundaries.

1. Thermal limit violation

If the demand along a feeder or at a substation is higher than its rating, the network congestion is defined as caused by thermal limit violation. The proposed charging envelope aims to help release stored energy for mitigating network pressure driven by overloading.

Based on typical household load and PV generation profiles in Figures 5-4, 5-5 and 5-6, the demand at feeder/substation level in each settlement period is

$$d_{sy,i} = d_{h,i} \cdot N \cdot cf \tag{5-7}$$

where, $d_{sy,i}$ and $d_{h,i}$ represent the demands at feeder/substation and household levels in the i^{th} settlement period. N stands for the number of customers connected to the specific feeder/substation, and cf is coincidence factor for load aggregation.

The overloading degree driven by thermal limit violation in each feeder/substation is firstly estimated by

$$L_{ol\_t} = d_{b\_t,p} - s_{ther} \cdot \cos\theta \tag{5-8}$$

where, $d_{b\_t,p}$ represents the peak demand along a feeder/transformer and s_{ther} is the thermal rating of the feeder/substation. $cos\theta$ represents the power factor.

The battery discharging power for resolving network congestion is determined by allocating network overloading to each household, considering their battery operation diversification.

$$R_{d\_t} = \frac{L_{ol\_t}}{N_{p,ol} \cdot cf_{dis}} \tag{5-9}$$

where, R_{d_t} is the required discharging power for overloading mitigation. $N_{p,ol}$ is the number of customers who use battery storage to participate in reliving network congestion, and cf_{dis} stands for the coincident factor for discharging distributed batteries.

During this overloading period, the additional storage capacity reservation of a storage battery to mitigate network pressure is

$$C_{ol\_t} = R_d \cdot T_{ol\_t} \tag{5-10}$$

where, T_{ol_t} represents the duration of the overloading driven by thermal limit violation.

2. Voltage limit violation

The acceptable voltage level along a feeder is normally from - 6% to +10% of the base value. If voltage is out of this range, networks congestion occurs, defined as driven by voltage limit violation. The per unit voltage drop along a feeder can be estimated with [88]

$$\Delta V \approx \frac{P \cdot R + Q \cdot X}{V} = \frac{S \cdot \cos\theta \cdot R + S \cdot \sin\theta \cdot X}{V} \tag{5-11}$$

where, P and Q are the per unit values of active power and reactive power along the feeder. V is the voltage at feeder head. R and X are per unit values of the resistance and reactance of the feeder.

The overvoltage level is defined by

$$\Delta V_{ol} = |\Delta V| - |\Delta V_{B,\min}| \tag{5-12}$$

where, $\Delta V_{B,min}$ is the maximum allowed voltage drop.

The overloading degree driven by voltage limit violation is

$$L_{ol\_v} \approx \frac{\Delta V_{ol} \cdot V \cdot S_B \cdot \cos\theta}{\cos\theta \cdot R + \sin\theta \cdot X} \tag{5-13}$$

where S_B is the base power.

Once the overloading level due to overvoltage is determined, the reserved capacity for mitigating overloading driven by over limit voltage drop is obtained by

$$C_{ol\_v} = \frac{L_{ol\_v}}{N_{p,ol} \cdot cf_{dis}} \cdot T_{ol\_v} \tag{5-14}$$

where, L_{ol_v} and T_{ol_t} represent the degree and duration of overloading caused by voltage limit violation.

Once additional reserved capacity to resolve network overloading is determined, an additional decrement of C_{ol_t}/C_{ol_v} in SoC is reflected in the upper boundary of a charging envelope.

5.5.2 Network Congestion Driven by Over Generation

In this case, charging envelopes should follow the variations of demand and PV generation in order to mitigate their adverse impacts on network thermal and voltage constraints. When solar generation is high, reverse power flow could cause voltage at feeder ends to violate the upper statutory limits. The reverse power flow from PV to substation also has the possibility to exceed feeder/transformer capacity and cause thermal limit violation. Therefore, an additional part of charging capacity needs to be reserved to reduce reverse power flow and mitigate the voltage or thermal violation. This should be reflected in the lower boundary of a charging envelope.

1. Thermal limit violation

Although there is a small chance that the reverse power flow could lead to a congestion driven by thermal limit violation, the required storage capacity reservation can still be quantified. The congested degree in this case is

$$L_{og\_t} = \left|d_{b\_t,rp}\right| - \left|s_{ther} \cdot \cos\theta\right| \tag{5-15}$$

Where $d_{b\_t,rp}$ represents the maximum reverse power flow through a feeder/substation.

Accordingly, the reserved capacity to mitigate the network pressure is

$$C_{og\_t} = \frac{L_{og\_t}}{N_{p,og} \cdot cf_{ch}} \cdot T_{og\_t} \tag{5-16}$$

Where cf_{ch} stands for the coincidence factor for charging distributed batteries and T_{og_t} is the duration of thermal limit violation of reverse power flow caused by over generation. $N_{p,og}$ is the number of customers participating in reliving network congestion caused by over generation.

2. Voltage limit violation

If the voltage along a feeder is higher than the maximum acceptable voltage rise, this congestion is defined as voltage limit violation driven by over generation. The over generation degree stems from the voltage rise above the maximum allowance is

$$L_{og\_v} \approx \frac{\Delta V_{og\_v} \cdot V \cdot S_B \cdot \cos\theta}{\cos\theta \cdot R + \sin\theta \cdot X} \tag{5-17}$$

where, ΔV_{og_v} is the difference between the maximum voltage increment along the feeder and the maximum acceptable voltage rise.

In the over generation period, the additional storage capacity reservation for network pressure mitigation is

$$C_{og\_v} = \frac{L_{og\_v}}{N_{p,og} \cdot cf_{ch}} \cdot T_{og\_v} \tag{5-18}$$

where, T_{og_v} represents the duration of over generation driven by voltage limit violation.

Once the additional reserved capacity to resolve the network pressure caused by over generation is determined, an increment of C_{og_t}/C_{og_v} in SoC can be reflected in the lower boundary of a charging envelope during the over generation period.

Generally, these network pressures in terms of overloading and over generation can be mitigated with energy storage operation by using the control approaches proposed in the follows.

5.6 Battery Charging Algorithm

Once the charging envelopes are determined, the follow-on work is to implement them for demand reduction and load shifting. The storage battery can respond to smart variable tariffs within the range confined by the charging envelopes to mitigate energy and network pressures.

As the charging envelope design has already taken network congestion and distributed generation into consideration, the main target of battery charging algorithm is to respond to energy price variation and then minimise the cost for purchasing electricity from main grid within a settlement day. In this study the impact of feed-in tariffs on financial cost savings is not considered. With the short term predictions of day-ahead load profiles and generation profiles, the optimization problem is formulated as:

1. Objective

$$\min \ C_{gr} = \sum_{i=1}^{48} e_i \cdot d_{new,i} \cdot t \cdot \alpha \tag{5-19}$$

where, C_{gr} is the total energy expense spent on purchasing energy from main grid. e_i denotes the tariff rate in the i^{th} settlement period within the employed smart variable tariffs, and $d_{new,i}$ represents the required power from main grid in the i^{th} settlement period. t is the length of each settlement period, which is 0.5 hour. α stands for the percentage of energy cost in electricity bills.

The required power supply from the main grid is determined by local AC and DC demands, and battery charging power after excluding PV generation. Therefore, the power from grid in the i^{th} settlement period is

$$d_{new,i} = \begin{cases} d_{h,i} + d_{DC,i} - g_{PV,i} + \dfrac{(S_{i+1} - S_i)}{t} & if \ d_{h,i} + d_{DC,i} - g_{PV,i} + \dfrac{(S_{i+1} - S_i)}{t} > 0 \\ 0 & Otherwise \end{cases} \tag{5-20}$$

Where $d_{DC,i}$ and $g_{PV,i}$ stand for household DC demand and the PV output of an array in the i^{th} settlement period respectively. S_i represents the SoC level in the i^{th} settlement period, and accordingly the difference between S_{i+1} and S_i is the battery charging/discharging amount during a settlement period.

2. Constraints

The constraints for the optimization problem are as follows.

i) The first constraint reflects that the sum of battery charging/discharging amount is zero within a day. Accordingly, the SoC at the end of a settlement day should be equal to that at the beginning of the day.

$$S_{49} = S_1 \tag{5-21}$$

ii) The second constraint presents that the SoCs of the battery should stay within the upper and lower boundaries in charging envelopes, given by

$$S_{lo,i} < S_i < S_{up,i} \tag{5-22}$$

Where $S_{up,i}$ and $S_{lo,i}$ are the maximum and minimum allowed SoCs in the i^{th} settlement period shown in the upper and lower boundaries of a charging envelope.

iii) The third constraint stems from the physical properties of battery storage, as the charging and discharging power should be within certain range determined by battery manufacturers. The potential charging and discharging powers should be subjective to

$$0 < S_{i+1} - S_i < p_{ch,li} \quad \text{(5-23,a)}$$

$$0 < S_i - S_{i+1} < p_{dis,li} \quad \text{(5-23,b)}$$

where battery charging and discharging power limits are denoted by $p_{ch,li}$ and $p_{dis,li}$ separately.

iv) The last constraint means that: i) in charging process (5-24.a), the actual charging power need to be higher that the SoC increasing rate confined by upper and lower boundaries of charging envelopes; ii) in discharging process (5-24.b), actual discharging power need to be higher than the SoC decreasing rate confined by upper and lower boundaries of charging envelopes.

$$S_{i+1} - S_i \geq \max(S_{up,i+1} - S_{up,i}, S_{lo,i+1} - S_{lo,i}) \quad \text{(5-24,a)}$$

$$S_i - S_{i+1} \leq \max(S_{up,i} - S_{up,i+1}, S_i - S_{lo,i+1}) \quad \text{(5-24,b)}$$

These constrains ensure that network congestion mitigation is included in charging envelope implementation. This formulated problem is a discrete optimisation with both objective and constraints being liner. This problem can be easily resolved by many software packages, for example CPLEX and fminconset based on Matlab. It solves constrained minimization problems where some of the variables are restricted to discrete values (Mixed Integer Nonlinear optimization). It is developed based on fmincon from Optimization Toolbox version 2.0 [114].

5.7 Benefit Quantification of Charging Envelope Implementation

For storage with shared ownership between customers and DNOs, the benefit from energy shift in response to smart variable tariffs will be combined with the benefit from charging envelope usage, forming whole-system benefits in terms of energy cost saving and network investment deferral. The total financial savings can be eventually expressed as unit price discounts for customers. The whole-system benefits quantification process is shown in Figure 5-10.

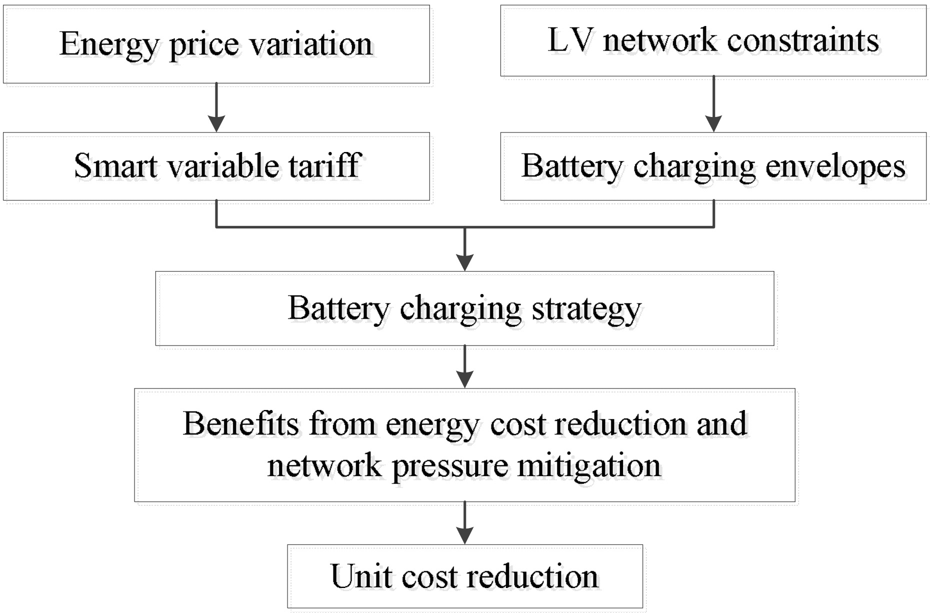


Figure 5-10 Flowchart of whole-system benefit quantification process

5.7.1 Whole-system Benefit Quantification

The annual whole-system benefits focus on three key parts:

1. Wholesale energy cost saving

The proposed smart variable tariffs are categorised by seasons and day types throughout a year. For each season, two types of tariffs will be designed for weekdays and weekends separately. Eventually, there will be eight scenarios of the variable tariffs for a whole year, to encourage energy consumption at appropriate times in different seasons.

The energy bills paid by customers are calculated by their electricity use from main grid in each settlement period and the corresponding energy prices. The benefits in terms of energy cost savings are calculated based on the new load levels after the conduction of the proposed energy management.

The energy consumption of a settlement year is calculated as the sum of daily energy usage, which is

$$D = \sum_{j=1}^{8} k_{day,j} \cdot (\sum_{i=1}^{48} d_{sy,i,j} \cdot t) \quad (5\text{-}25)$$

Where $d_{sy,i,j}$ represents the system load of the i^{th} settlement period in the j^{th} scenario, and $k_{day,j}$ is the total number of days within the j^{th} scenario over a year.

Accordingly, the total energy cost is assessed by

$$C_{en} = \sum_{j=1}^{8} k_{day,j} \cdot (\sum_{i=1}^{48} e_{i,j} \cdot d_{sy,i,j,} \cdot t \cdot \alpha) \quad (5\text{-}26)$$

Where $e_{i,j}$ is the smart variable tariff rate of the i^{th} settlement period in the j^{th} scenario. Based on the system load profiles before and after EMS application, the wholesale energy cost saving is

$$\Delta C_{en} = C_{en,ori} - C_{en,new} \quad (5\text{-}27)$$

Where $C_{en,ori}$ and $C_{en,new}$ are the annual energy costs before and after energy management by charging envelopes and smart variable tariffs.

2. Network investment cost saving

The benefit from network investment deferral is determined by examining the peak demand reduction and the time delay in network assets' future investment. The time delays are then translated into network benefits.

By employing Long-run Incremental Cost (LRIC) charging method [89], the investment horizon under a given load growth rate can be identified with

$$n = \frac{\log RC - \log D}{\log(1+r)} \tag{5-28}$$

where, *RC* is the rating, *r* is selected load growth rate and *D* is system peak demand.

The network cost saving ΔC_{ne}, which is expressed as the change in present value along with investment horizon increment, is

$$\Delta C_{ne} = \Delta PV = Asset\_Cost \cdot \left(\frac{1}{(1+d)^{n_{new}}} - \frac{1}{(1+d)^{n}} \right) \tag{5-29}$$

where, *d* is the discount rate, *n* is the original reinforcement horizon and n_{new} is the new reinforcement horizon caused by peak reduction.

3. Other saving and total benefit:

The total financial benefits are the sum of the financial savings from the wholesale energy cost, network investment cost and other costs. Therefore, the total electricity cost of a settlement year is

$$\Delta C_{total} = C_{total,ori} - C_{total.new} \tag{5-30}$$

Where $C_{total,ori}$ and $C_{total,new}$ are the total financial costs before and after energy management implementation, given as

$$C_{total} = \sum_{j=1}^{8} k_{day,j} \cdot (\sum_{i=1}^{48} e_{i,j} \cdot d_{sy,i,j,} \cdot t) \tag{5-31}$$

Then, the benefit from other factors, such as the saving from environmental charges, can be obtained by

$$\Delta C_{ot} = \Delta C_{total} - \Delta C_{en} - \Delta C_{ne} \tag{5-32}$$

5.7.2 Unit Price Reduction for End Users

In order to convert the total benefit to unit price reduction for customers, the per unit costs in electricity before and after energy management need to be quantified firstly.

The unit rate is expressed as the quotient of total electricity bill and energy consumption from main grid, expressed as

$$R = \frac{C_{total}}{D} \tag{5-33}$$

Where R represents tariff rate.

The electricity price discount is eventually evaluated by

$$PD = \frac{(R_{ori} - R_{new})}{R_{ori}} \cdot 100\% \tag{5-34}$$

Where R_{ori} and R_{new} represent the costs of per unit energy consumption before and after energy management separately.

5.8 Case study

In this section, a practical distribution network is employed to demonstrate the developed charging envelopes and quantify the impact of energy management on financial savings. The investigation is conducted on eight typical days which represent weekdays and weekends of the four seasons respectively. Annual benefit for the whole system is quantified at the end of this section.

5.8.1 Test Network

A practical radial LV network in Illminster Avenue is chosen for case study in Figure 5-11 [90]. The parameters of the test network, including feeder lengths and transformer capacities, have been given in Table 4-2 and Table 4-3. The unit impedance of all feeders is 0.939+j0.076 (Ω/km). Power factor and coincidence factor of load aggregation are 0.95 and 0.8 respectively [91].

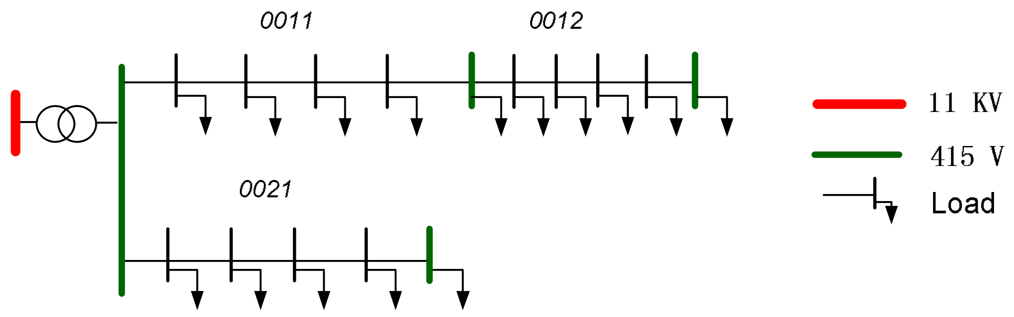


Figure 5-11 Layout of a radial LV network in Illminster Avenue

There is an assumption that all the customers under the distribution system are residential households with similar load profiles and the same size of PVs and batteries. Generation profiles in Figure 5-6 are assumed as the average values for the four seasons. By analysing PV generation samples from [109], the standard deviation of the samples is calculated as 1.03 and the confidential interval is assumed as 0.95. The coincidence factor for battery charging and discharging are both assumed as 0.8.

5.8.2 Parameters of Household Distributed EMS

In order to investigate how in-home batteries can help customers to manage their energy usage and solve network problems when a number of customers connect PV solar panels to their house, an assumption is made that the penetration level of the household distributed EMS in the test network is 100% . For each individual EMS integrated with PV and storage battery, the parameters are listed in Table 5-1. The battery configuration referenced here consists of 4×100Ah 12V DC battery cells, and the capacity of battery and PV are 4.8kWh and 3.5kWp respectively [86].

Table 5-1 Parameters of a distributed PV and storage battery

	Unit
Battery capacity	4.8kWh
Battery charging current limit	<20% of rated AmpHours
Battery discharging current limit	<20% of rated AmpHours
PV array size	3.5 kWp

5.8.3 Charging Envelope without Network Congestion

In the test system, the present transformer utilization is 43%, and there is no network congestion in the whole system with time-series power flow analysis. Therefore, the charging envelopes designed for all customers are identical for energy management. The charging envelope design is linked to not only customer demand and local PV generation, but also the parameters of household EMS. Using these inputs, the charging envelopes which can accommodate all the storages in the system for weekdays and weekends in different seasons on are as shown in Figures 5-12 and 5-13 respectively. The eight broken lines shown in these two figures are the upper boundaries of the charging envelopes designed for different day types within a year. Meanwhile, the lower limit, depicted with dark grey straight line, represent the lower boundary of these charging envelopes. For both upper and lower boundaries, the initial and ending points of each line can be easily connected ,which means the SoC at the end of a day is equal to the beginning SoC of the next day.

Among these different upper boundaries, it can be observed that the maximum allowed SoCs during daytime charging periods (Period 3) vary dramatically with seasons. In another word, the reserved capacity for battery charging from PV in summer is around four times as much as that in winter for efficient use of distributed generation. The decreases of SoCs in upper boundaries in the evenings illustrate that the reserved storage capacities for discharging from 16pm onwards are similar in all the four seasons. It is due to the fact that the total amount of discharged energy is primarily used to support local DC load instead of mitigating network congestion. In low PV output seasons, such as winter, the maximum allowed SoCs have increments of 8% before 6am on weekdays and 12% before 10am on weekends. It means a portion of energy absorbed from main grid during overnight charging period (Period 1) is essential under such weather condition in addition to day-time PV charging. In contrast, the decrements of the maximum SoCs before 10am in other seasons are up to 22% in order to prepare for day-time PV charging.

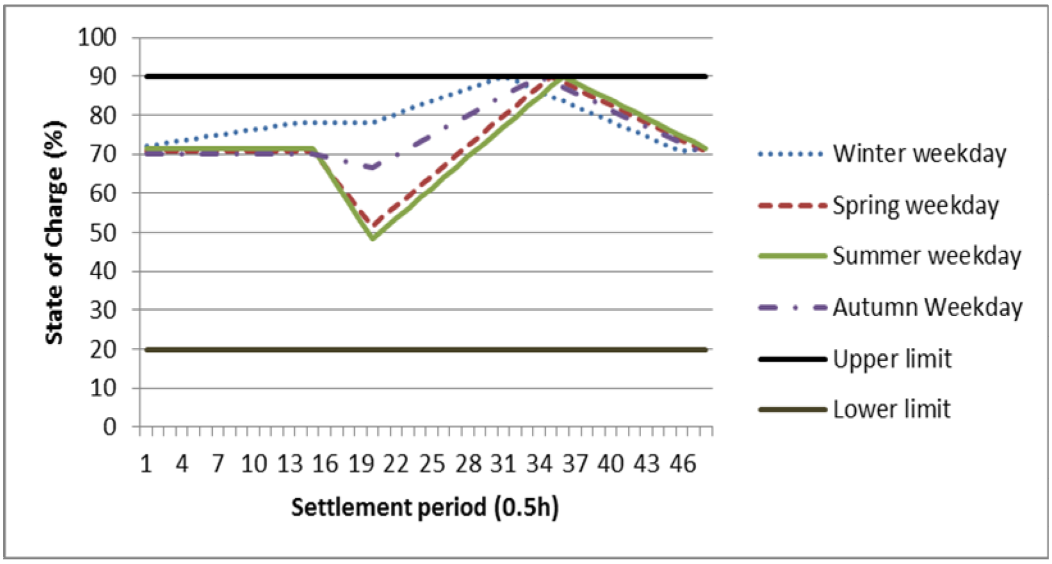


Figure 5-12 Charging envelopes for distributed storages without network congestion at weekdays

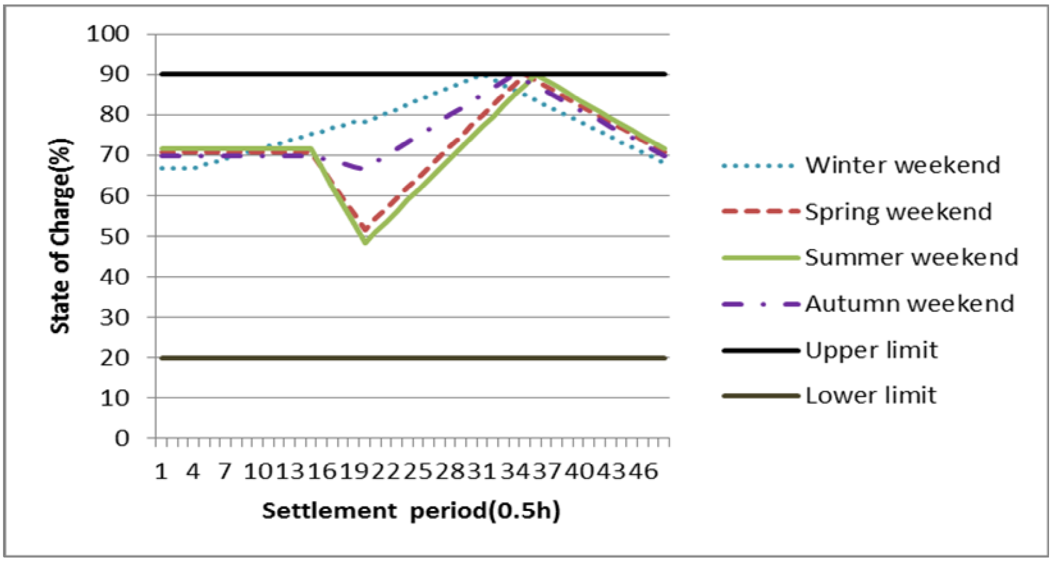


Figure 5-13 Charging envelopes for distributed storages without network congestion at weekends

If the charging envelopes designed for weekdays are compared with those for weekends, there are slight differences in the charging slopes and the time windows. As the predicted PV generation at weekdays and weekends are assumed identical, day-time charging periods and constrains reflected in upper boundaries are the same. The overnight charging period in winter weekends starts later than the period in winter weekdays. This is simply because of load profile changes in different day types.

5.8.4 Charging Envelope with Network Congestion

This section demonstrates the charging envelope designs with forecasted network congestions. The results are compared with those in the case without network congestion in Section 5.8.3.

Based on the assumed load growth rate of 2%, the time-series power flow shows that there will be thermal limit violations along feeders 0011 and 0021 in the early evenings of winter in the 10^{th} year. Due to different degrees and durations of overloading along different feeders, one type of charging envelope is inappropriate to be applied to all storages for network pressure mitigation or energy management. The charging envelopes for batteries connected to different branches with different network pressures should be designed separately. In the test system, due to different numbers of customers connected to these two branches, two types of charging envelopes are designed for winter weekdays, shown in Figure 5-14. Similarly, Figure 5-15 illustrates the two charging envelopes if the case is at winter weekends.

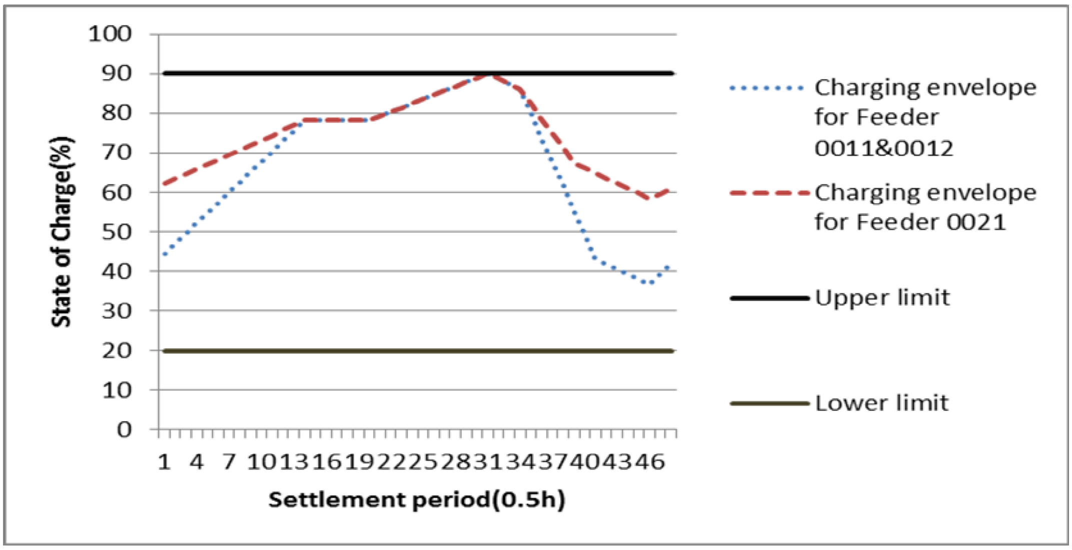


Figure 5-14 Charging envelopes for winter weekdays with overloading case

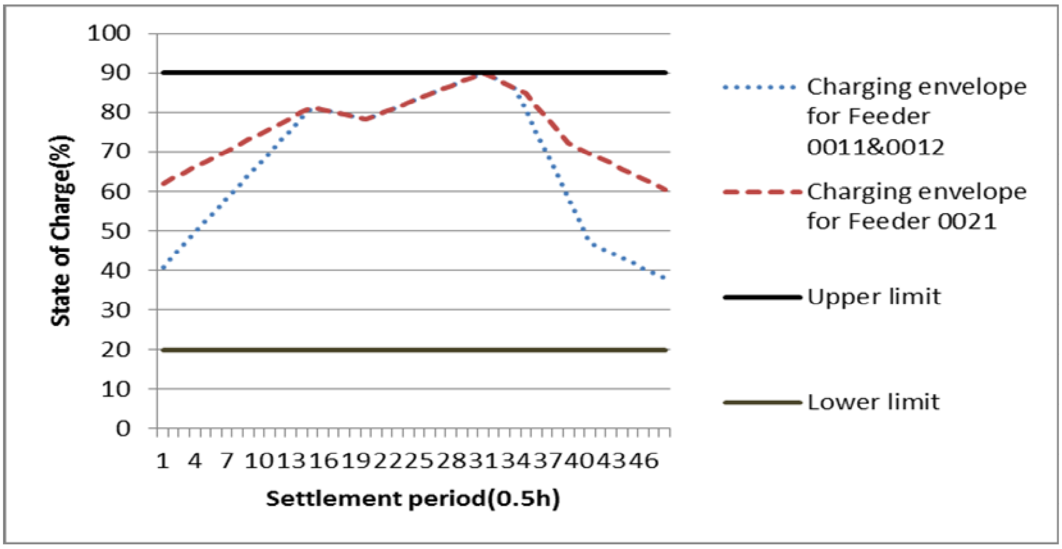


Figure 5-15 Charging envelopes for winter weekends with overloading case

Compared with the charging envelopes for winter without congestion, there are dramatic decreases of SoCs from 17pm onwards in upper boundaries for all the charging envelopes designed for weekdays and weekends, showing by the dot line and dash line in Figures 5-14 and 5-15. These decrements represent the increments of storage capacity reservation which are used to overcome overloading during congested periods. Based on the obtained charging envelopes, the capacity of storage reserved for network mitigation along feeders 0011&0012 is 43%, which is around twice as much as the reservations in feeder 0021 (19%). It is due to higher degree and longer duration of overloading in feeder 0011 under the test condition.

For each feeder, the decrements of SoC in the upper boundary during congested period in winter weekdays and weekends only have slight differences, ranging from 4% to 6%. The reason lies in the same lengths of congested periods and the similar levels of congested degrees at weekdays and weekends.

The charging envelopes designed for mitigating the congestions driven by over generation of PV in summer are shown in Figures 5-16 and 5-17. They are designed based on the assumption that the voltage at the substation is 1.075p.u and the PV generation is at the maximum confidence. These charging envelopes are only required for the storages connected to feeders 0011 and 0012, as only the voltages along this branch are out of statutory range.

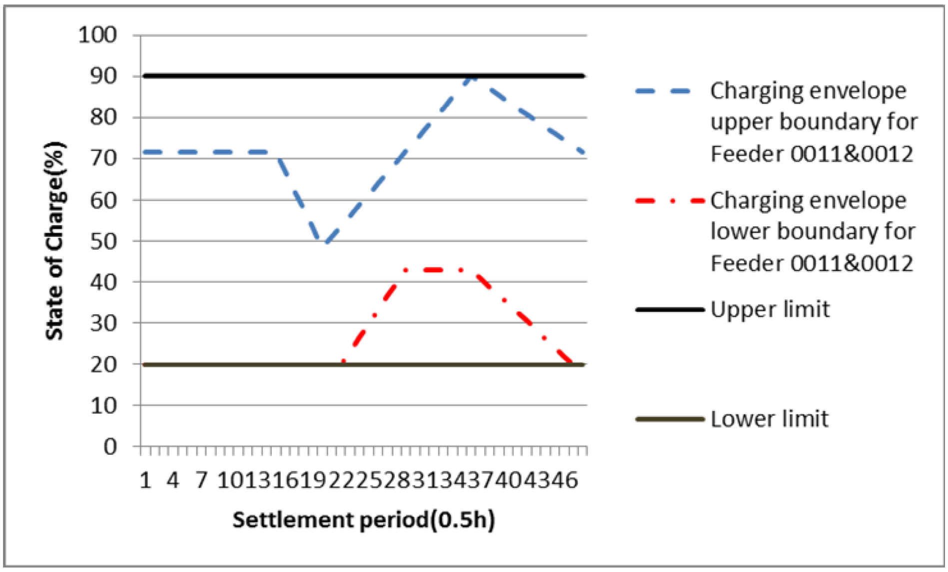


Figure 5-16 Charging envelope design for summer weekdays with over generation case

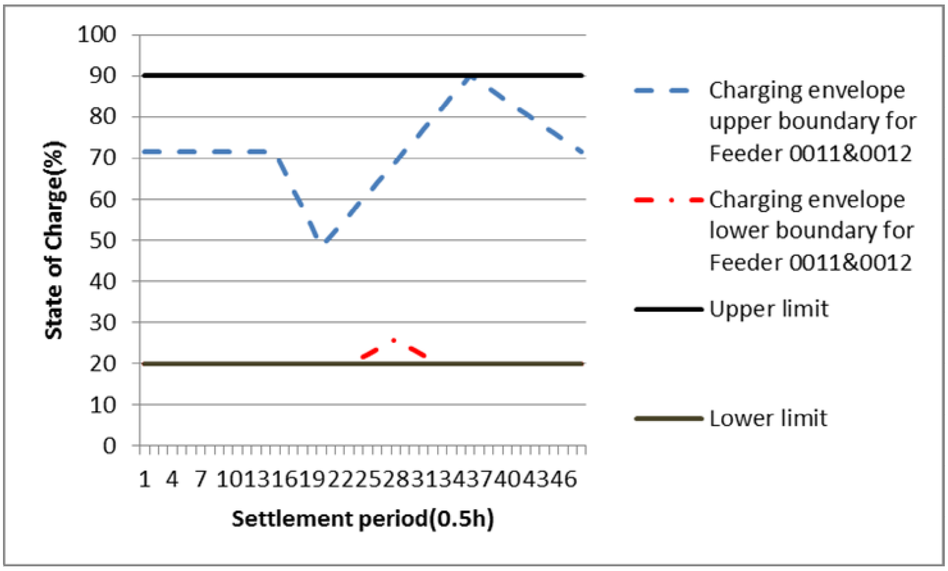


Figure 5-17 Charging envelope design for summer weekends with over generation case

The red dash dot line in Figure 5-16 shows that from 10:30am to 14pm, the lower boundary of SoC increases from 20% to 43%. Thus, the storage capacity reserved to avoid voltage rise due to larger PV generation and lower demand is the difference between these two values, leading to 23%. The capacity reservation for battery charging to avoid over generation at summer weekends is only 5.8%, which is far less than the reservation amount for weekdays. Accordingly, it can be found that the voltage rises due to reverse power flows at weekdays are generally higher than those at weekends.

5.8.5 Charging Envelope Implementation

Once the charging envelopes are determined, the following task is to identify how system load profiles would change with the proposed storage operation scheme. The initial SoC of battery in the system is random, which can be assumed to follow a normal distribution within the range defined by charging envelope shown in Figure 5-18.

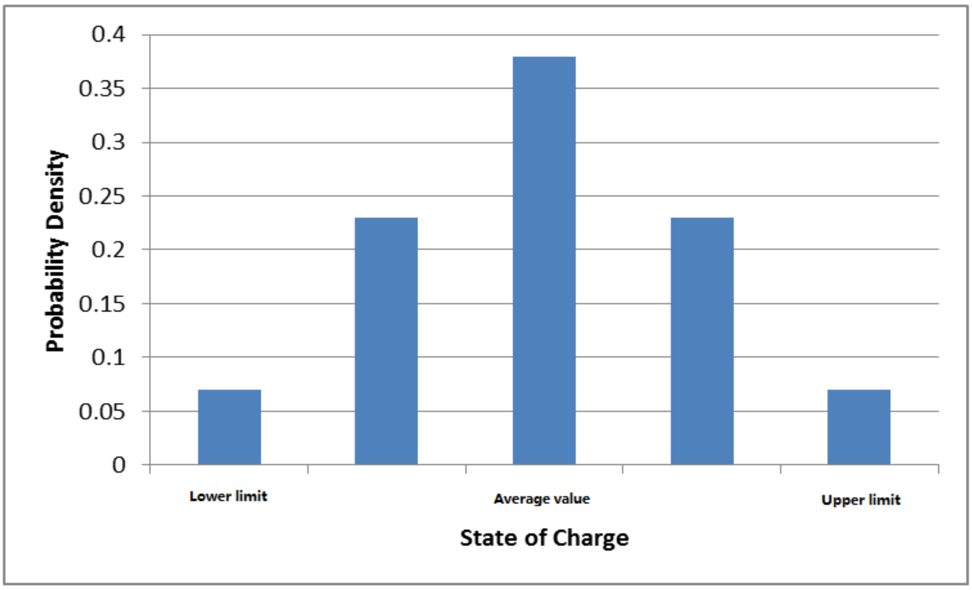


Figure 5-18 Initial SoC distribution

1. Smart variable tariff determination

Theoretically, in order to realise the response to energy price variation, RTP tariffs can be adopted to reflect energy price and quantify energy cost saving accurately. However, a currently designed household EMS by SIMENS [115] can only accommodate three price categories at most. Therefore, the first task in charging envelope implementation is to explore the effect of RTP and TOU in peak demand reduction and energy cost saving. The RTP and TOU tariffs, which are capable of reflecting energy price variation, have been developed in Chapter 3. The sequence of TOU tariffs achieved by equal interval grouping method is selected here for charging envelope implementation.

Winter weekday is taken as a test example to demonstrate the effect of TOU and RTP. Figures 5-19 and 5-20 takes substation load level as an example to show the results from the implementations of charging envelopes coupled with RTP and TOU tariffs respectively.

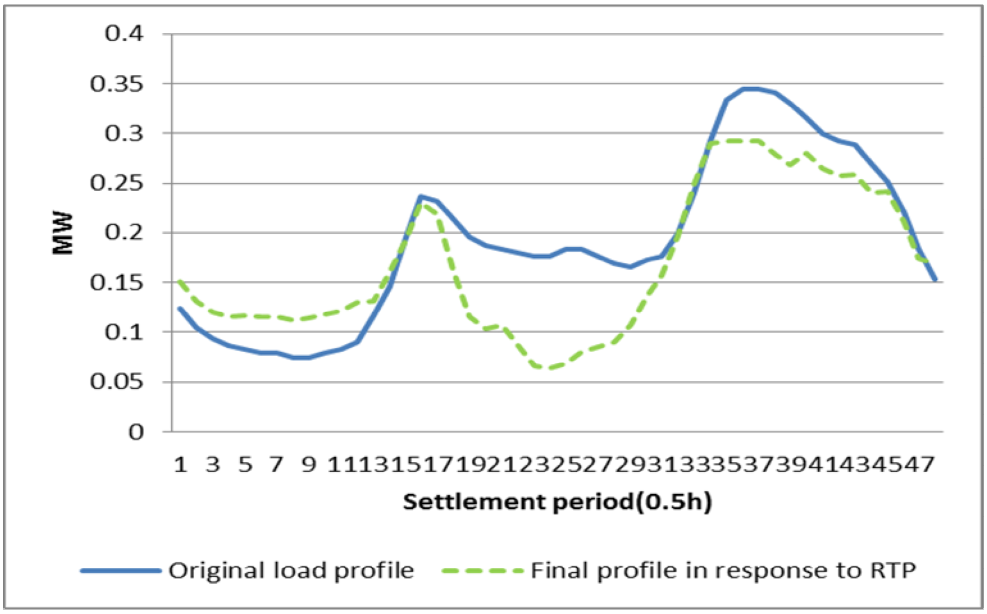


Figure 5-19 Original loads and shifted load in response to RTP

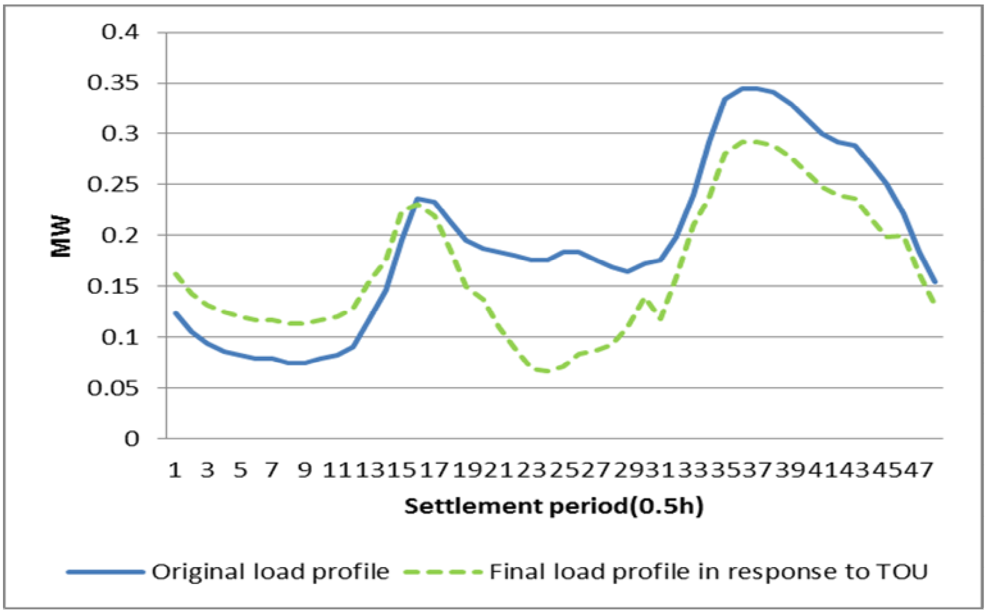


Figure 5-20 Original loads and shifted load in response to TOU

In these two figures, the blue solid lines are the original load profiles of the test substation. When energy storage batteries are used to respond to the RTP or the TOU tariffs respectively, the shifted loads, shown as green dash lines, are almost the same for both situations. The peak demands of the two profiles after load shifting are 0.293MW and 0.294MW respectively.

Any slight differences in load shifting may cause difference in energy cost saving for customers. The comparison results for the whole system benefit are listed in Table 5-2. The cost savings are very close with RTP or TOU as input signals. For all the customers under the test system, the energy cost saving from load shifting in response to RTP is £48.54, while the saving is £48.36 per day under TOU. The difference is only £0.18 per day for the whole test system with 257 customers. Accordingly, the daily cost saving per household under RTP is 18.88 pence, and it will be 18.81 pence if the response is subject to TOU. The difference is only 0.08 pence per day for each household.

Table 5-2 Comparison of energy cost saving between RTP and TOU

	Whole-system energy cost saving(£)	Household energy cost saving (pence)
Cost Saving (RTP)	48.54	18.88
Cost Saving (TOU)	48.36	18.80
Difference between RTP and TOU	0.18	0.08

In the test network of Iliminster Avenue, the results show that as input signals for energy storage batteries, the developed TOU act a very similar role to RTP in peak demand reduction and energy cost saving. Therefore, the TOU tariffs with three price-steps can be accurately used as input signals instead of RTPs.

2. Implementation without network congestion

With employing the battery charging algorithm proposed in Section 5.6, demand reduction and load shifting are expected in the whole system. When there is no network congestion, the original load profiles at the substation level and the profiles after implementing charging envelope at weekdays and weekends are shown in Figures 5-21 and 5-22 respectively. The original load profiles are depicted with solid blue lines and the final profiles are represented by dash green lines. According to these two groups of load profiles, the most obvious load profile change with implementing the proposed charging envelope is dramatic demand decrement during daytime. The profiles of spring, summer and autumn even show negative values which represent reverse power flows caused by PV generation. In the eight illustrated scenarios, there are different degrees of peak demand reductions in the evenings and less obvious demand increments in the early mornings. Accordingly, the consequent benefits in terms of peak demand reductions and energy cost savings are shown in Table 5-3. The daily peak demand reductions over the four seasons range from 0.033 MW to 0.062 MW and the most effective peak shaving occurs at spring weekdays. Overall, the annual peak demand in the whole system is reduced from 0.345 MW to 0.302 MW.

Along with demand reduction and load shifting, the daily energy costs have decrements as well, ranging from £48.36 to £136.17. The two main factors that generate the maximum financial benefit in spring are sufficient PV generation and less inexpensive energy price level during that season.

Table 5-3 Summary of benefit for charging envelope implementation under no network congestion condition

	Peak demand reduction(MW)	Energy cost saving(£)
Winter weekday	0.052	48.36
Spring weekday	0.062	126.68
Summer weekday	0.033	114.88
Autumn weekday	0.051	98.47
Winter weekend	0.038	56.09
Spring weekend	0.056	136.17
Summer weekend	0.058	125.49
Autumn weekend	0.038	117.36

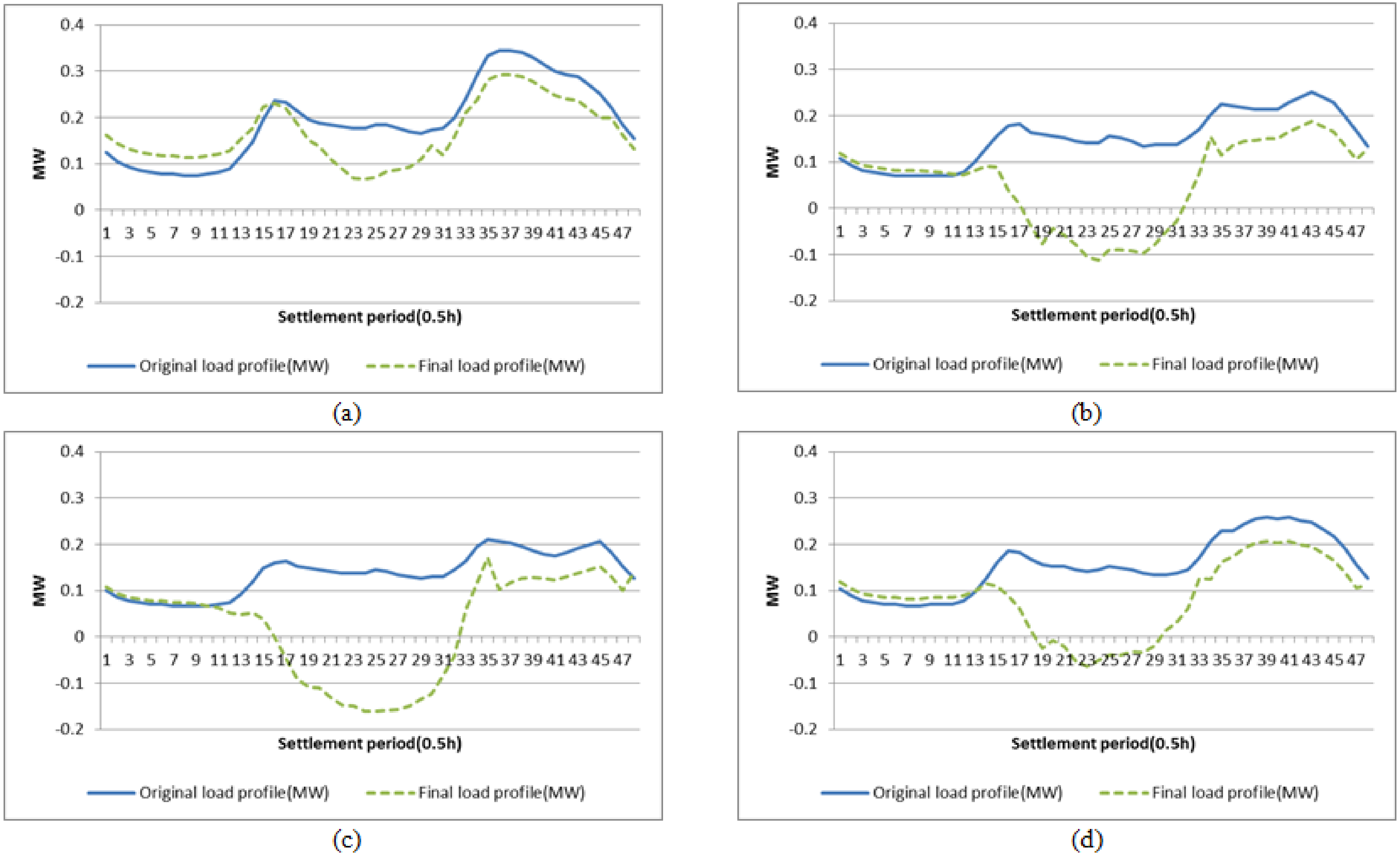


Figure 5-21 Aggregated load profile change at weekdays under the condition without network congestion: (a) winter, (b) spring, (c) summer, (d) autumn

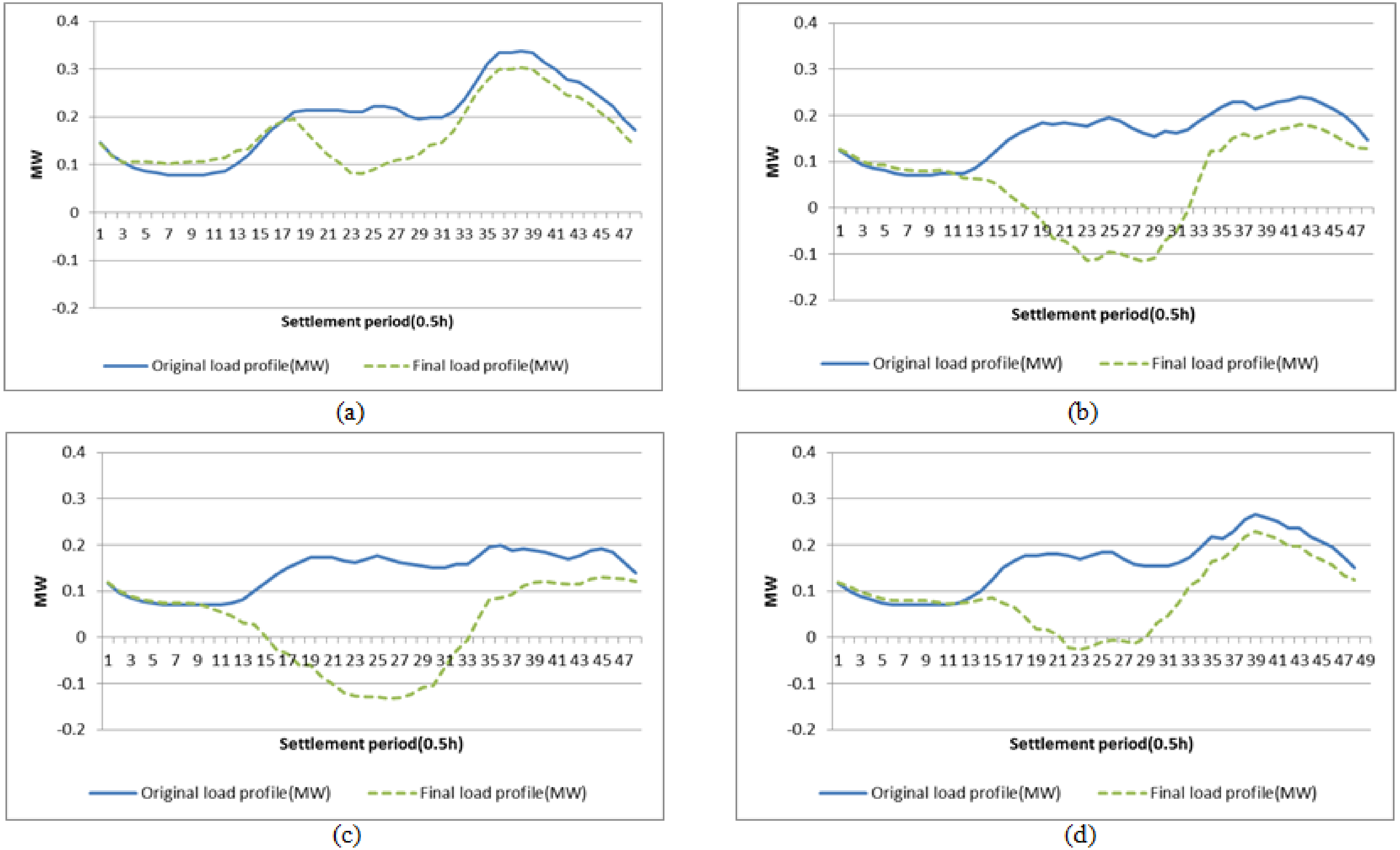


Figure 5-22 Aggregated load profile change at weekends under the condition without network congestion: (a) winter, (b) spring, (c) summer, (d) autumn

3. Implementation with network congestion

Figures 5-23 and 5-24 demonstrate load profile change due to the implementations of charging envelopes designed for overloading conditions on winter weekdays and weekends. In contrast, the changes of load profiles in summer are illustrated in Figures 5-25 and 5-26. Meanwhile, the impacts of charging envelope application on peak shaving and energy cost saving are quantified in Table 5-4.

The load profile change in winter shows peak reductions of 0.082 MW on a typical weekday and 0.069 MW on a weekend. These reductions are nearly twice those observed in Figure 5-21 (a) and 5-22 (a). The increases of the peak reduction degrees are mainly due to the increments of energy storage reservations during peak hours.

The network congestions caused by over generation in summer are simulated with the PV generation at the maximum confidence. Even though the charging envelopes with storage capacity reservation for PV charging have been applied to reduce reverse power flow and voltage rise at feeder ends, the load profiles after energy management still have a great amount of reverse power flow up to -0.27 MW. Anyhow, the voltage limit violations are mitigated in the congested circuit with the voltage reductions of 1.45% and 0.36% at feeder ends for weekdays and weekends separately.

In addition, the energy cost savings from charging envelope implementation with network congestions are summarised as well. The daily benefits from overloading mitigations in winter range from £74.55 to £81.42, and the cost saving along with the reliefs of network congestions driven by over generation are calculated as £133.27 for a summer weekday and £152.34 for a weekend. Compared with the benefit assessment for the cases without congestions shown in Table 5-3, more energy cost savings can be achieved under the conditions with network congestions.

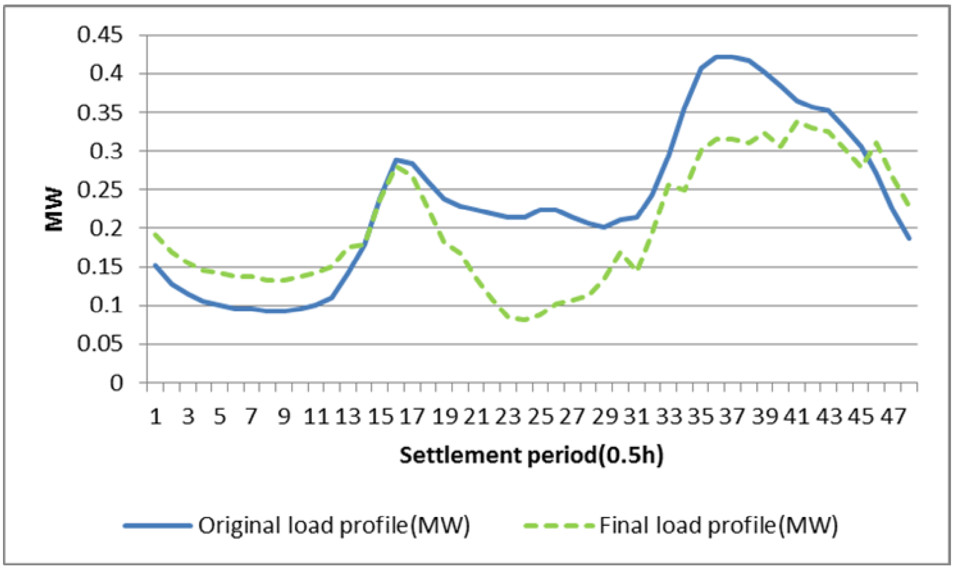


Figure 5-23 Aggregated load profile change under the condition with over loading at winter weekdays

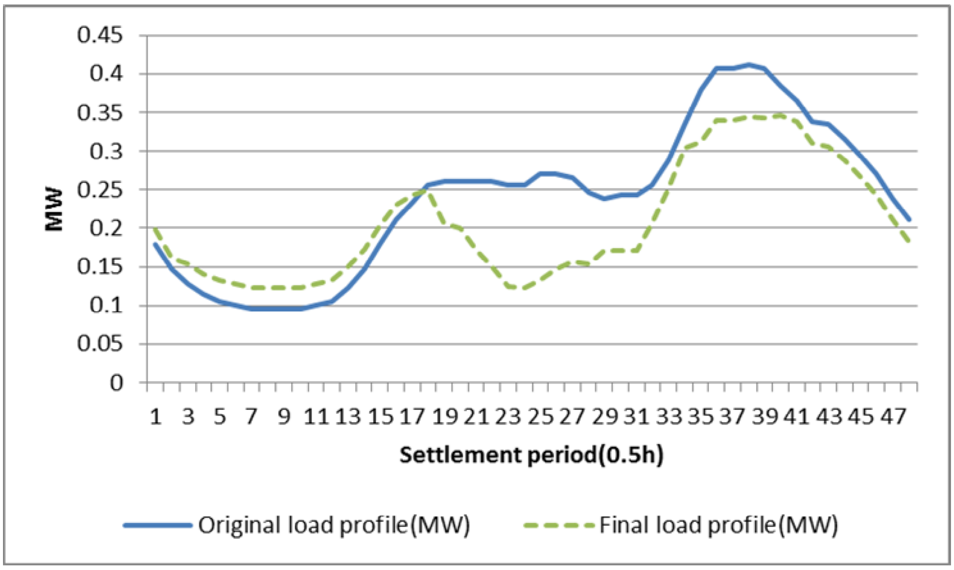


Figure 5-24 Aggregated load profile change under the condition with over loading at winter weekends

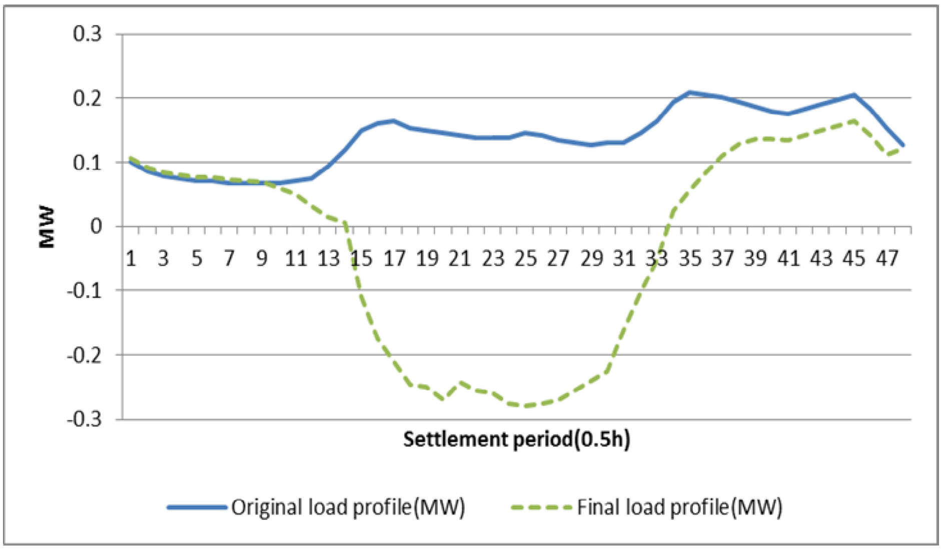


Figure 5-25 Aggregated load profile change under the condition with over generation at summer weekdays

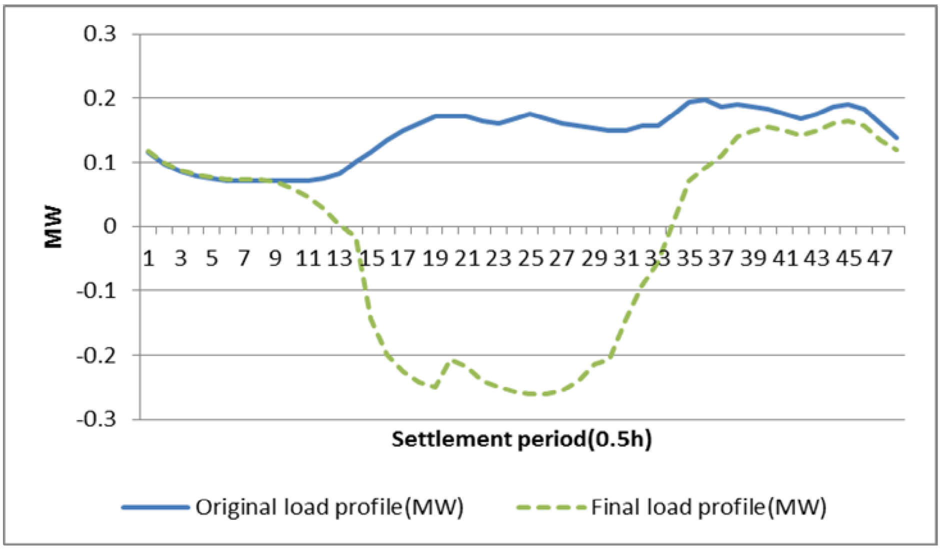


Figure 5-26 Aggregated load profile change under the condition with over generation at summer weekends

Table 5-4 Summary of benefit for charging envelope implementation under network congestion condition

	Peak demand reduction(MW)	Energy cost saving(£)
Winter weekday	0.082	62.69
Winter weekend	0.069	71.26
Summer weekday	0.041	117.30
Summer weekend	0.027	137.27

5.8.6 Benefit Quantification

Based on the degrees of peak demand shaving and energy cost saving with charging envelope implementation, financial cost savings are quantified for eight typical scenarios. Annual benefit is estimated by accumulating the cost savings in each scenario.

For the whole system of Illminister Avenue, the benefit quantification of each component in electricity bill is as shown in Table 5-5. The total electricity cost over a year is evaluated with a reduction of £66,483. Accordingly, annual energy consumption from main grid in the whole system decreases from 1,450 MWh to 933 MWh. Therefore, if the total financial benefit is averagely assigned to per unit energy consumption, the rate of the smart fixed tariff will be reduced from 10.2 p/kWh to 8.7 p/kWh.

Table 5-5 Cost and tariff rate comparison at Illminister Avenue substation level

	No PV & storage	With PV & storage	Cost saving
Annual energy from grid (MWh)	1450	933	
Wholesale energy cost	81,025	44,459	36,566
Distribution charges (£)	26,517	14,550	11,967
Transmission charges (£)	7,366	4,042	3,324
Other cost (£)	32,410	17,784	14,626
Total electricity bill (£)	147,318	80,835	66,483
Tariff (p/kWh)	10.2	8.7	

Under the test condition, individual benefit for each household connected with the Illminister Avenue network is estimated by averaging the total benefit at substation level. Eventually, the electricity bill saving from the proposed energy management is £259 per household as shown in Table 5-6.

Table 5-6 Cost and tariff rate comparison at household level

	No PV & storage	With PV & storage	Cost saving
Annual consumed energy from grid(kWh)	5643	3630	2013
Total electricity bill(£)	575	314	259
Tariff(p/kWh)	10.2	8.7	

The quantified benefits in this section depend on predicted AC/DC loads and PV outputs, and their consequential impacts on the network pressures greatly. Besides, the smart variable tariffs which are fundamentally designed based on energy price variation also contribute to the results. The amount of discount that customers will benefit is directly linked to the whole-system benefits from integrated energy management with PV and storage battery.

Therefore, for the test system, there is a 14.7% cut in tariff rate against a baseline of 10.2 p/kWh. If this percentage of tariff reduction is applied to the most common tariff in GB which is 17 p/kWh, the unit rate will drop from 17 p/kWh to 14.5 p/kWh for end users.

5.9 Chapter Summary

This chapter proposes an innovative approach to enhance energy management for energy cost minimization and network constraint mitigation. The new concept of charging envelop is proposed to manage the SoC of storage battery, mitigate network pressure and take advantage of PV generation. Generally, it is characterised by indicating the amount of energy available for charging and discharging with the consideration of distribution network pressures. The application of charging envelope is cooperated with smart variable tariffs for financial benefit. An optimised battery operation strategy is designed via the correlation between them. Eventually, the total benefit obtained from the proposed energy management scheme will be expressed to customers as a discount on a fixed tariff.

In the process of charging envelope design, in order to mitigate network pressure under heavy load condition, such as in winter, a portion of storage capacity will be reserved for discharging and it is reflected as a decline on upper boundary. For improving the operation of network with plenty of PV output in summer, an increasing slope on lower boundary is essential to force battery charging and avoid voltage limit violation at the feeder end.

The demonstration of the proposed method has proved that the energy management with charging envelope is effective for both energy cost and peak demand reductions. In the test system, daily energy cost savings range from £40 to £140 with the proposed method. Meanwhile, 15% of peak demand is able to be shaved. If the network does happen to be congested, the enhanced battery management would lead to further increments of energy cost saving amount and peak load shaving degree. When the final benefit is converted into the discount of per unit cost, there will be a reduction of 14.7% from the original tariff rate.

Chapter 6

Extending Storage Solution to Social Solution for Effective Demand Response

THIS chapter evaluates domestic demand shifting in response to smart variable tariffs. The value of it is quantified as an equivalent storage capacity for the investigation of complementarity between technical and social interventions.

6.1 Introduction

The effects of DSR triggered by distributed storage battery have been investigated in Chapter 4 and Chapter 5. In addition to the storage solutions which are able to shift demand from peak to trough periods, the shifting of household appliances could also play a part in DSR, particularly those wet appliances such as washing machine and dish washer. Meanwhile, the storage technology based demand shifting could be concentrated for highly inflexible demand such as lighting and entertainment. This investigation is carried out to understand the opportunities and benefits from a combination of technology and social based load shifting.

This chapter presents the evaluation of household demand shifting to investigate its impact on financial saving based on smart variable tariffs. Annual benefits are quantified at both household and distribution system levels. Besides, the performance of DSR enabled by domestic demand shifting is compared with that facilitated by energy storage as benefit assessment from social and technical sides. Their cooperation on demand shifting could lead financial benefit improvement for end users.

6.2 Problem and Proposed Solution Statement

Battery storage is able to be charged or discharged in appropriate time intervals in response to energy price signals and demand levels for energy cost reduction and network pressure mitigation. With the development of advanced energy storage technologies, responses from distributed energy storages for their participation in energy and network managements have attracted a number of investigations. Besides the studies in the last two chapters, references [107, 116-118] also focus on DSRs from storage implementations. However, the potential of extending DSR from energy storage to other aspects was not considered. This chapter carries out a study to investigate DSR from feasible household demand shifting.

Generally, customers are encouraged to change their energy use by taking advantage of low energy prices. Two main type of approaches are proposed in [31] to flatten load profiles and then reduce/defer needed network investment:

i) reducing overall demand;

ii) shifting existing load.

As load shifting is not only capable of bringing fewer interruptions to normal energy consumptions, but also effective in avoiding energy usage in peak periods and using existing generating plants and network capacity efficiently. Therefore, in order to assess the impact of household demand shifting, load modelling is needed to estimate the consequential benefits from effective load shifting.

For typical GB domestic customers, electricity is majorly required for heating, cooking, lighting and other electric appliances. Ideally, each composition of the consumption could be shifted to alter load profiles. The impact of a load shifting on electricity bill reduction depends on the degree and duration of it. However, there is a limited scope for domestic consumers' responses. The flexibilities and capabilities of household appliances used for shifting are shown in Figure 6-1. Since heating, cooking and lighting are essential for daily life, shifting them to other time slots is almost impossible for general users. Accordingly, they are regarded as inflexible loads. By contrast, the shifting of wet appliances, such as dishwashers, washing machines and tumble dryers in domestic sector, is likely to result in the least disruption to daily life [119]. Moreover, wet appliances consume about 15% [119] of the total electricity for a typical household. Therefore, wet appliances, as flexible loads, can be used for effective load shifting. Meanwhile, energy storage systems are able to manage the inflexible loads that are unlikely to be changed by people voluntarily. Therefore, the independent management of flexible and inflexible loads contributes to greater demand response for energy cost reduction and network reinforcement saving.

Compared to existing work on household energy storage and appliance operations, this chapter has the following three key contributions:

i) proposing an innovative flexible load shifting algorithm based on energy price variation and residents' daily life habits;

ii) evaluating financial benefit from household demand shifting and quantifying an equivalent storage capacity;

iii) estimating the potential benefit from DSR enabled by the cooperation of energy storage and flexible load shifting for the investigation of complementarity between technical and social interventions.

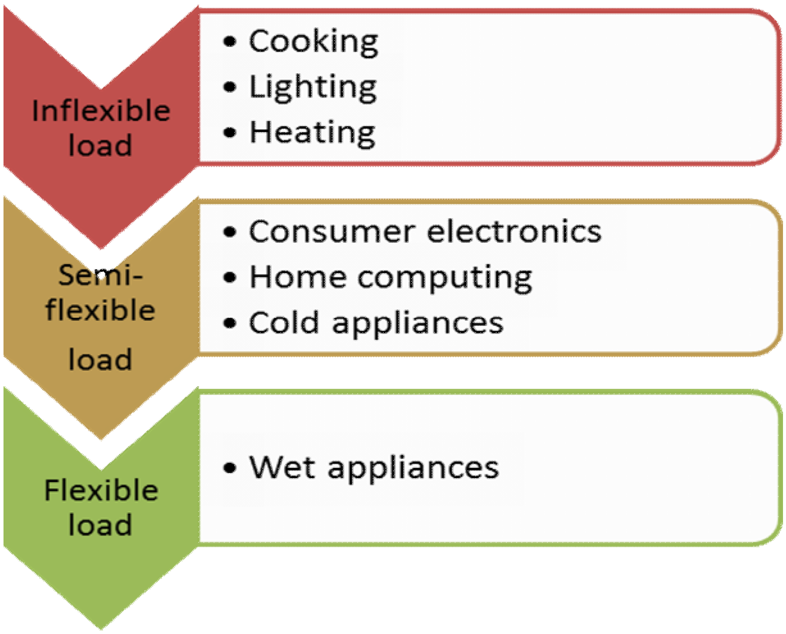


Figure 6-1 Flexibility of household appliance

The reminder of the chapter is organised as follows: Section 6.3 describes the modelling of flexible loads. Section 6.4 presents the algorithm of flexible load shifting and the associated method for benefit quantification is proposed in Section 6.5. Section 6.6 explores the benefit from effective DSR which is enabled by the cooperation between energy storage and household demand shifting. Section 6.7 evaluates the financial benefits for a practical LV distribution system. Eventually, conclusions are drawn in Section 6.8.

6.3 Flexible Load Modelling

In order to assess the impact of household demand shifting on whole-system benefit, a bottom-up approach is adopted to aggregate load profiles for LV substations from households. For a typical household, the individual load profile of each wet appliance is chosen from [120], showing the power in each time slot. In order to reflect the diversity of energy consumption, three typical household profiles [121,122], which reflect different start running times of the wet appliances, are selected for modelling. The first type represents the customers who use wet appliances mostly in the evening. The second and the third types stand for the cases that wet appliance usages occur in the morning and evening separately. The profiles for the flexible loads are shown in Figures 6-2, 6-3 and 6-4. Generally speaking, they have two obvious features:

i) The wet appliances are usually used after lunch or supper.

ii) The tumble dryers are always used following washing machines.

Once the individual load profile of each appliance is modelled, the profiles at substation level can be obtained by aggregating them. It is assumed that the household numbers of the three dwelling types are the same. For each type of household, the flexible loads are expected to be shifted to off-peak periods. Theoretically, customers could implement load shifting in response to real-time variable tariffs which are able to reflect wholesale energy price variations [123]. However, due to the frequent changes of the real-time prices, it is difficult for customers to find suitable time intervals to shift flexible loads appropriately. Therefore, appropriate tariffs are essential for wet appliances as incentives for load shifting.

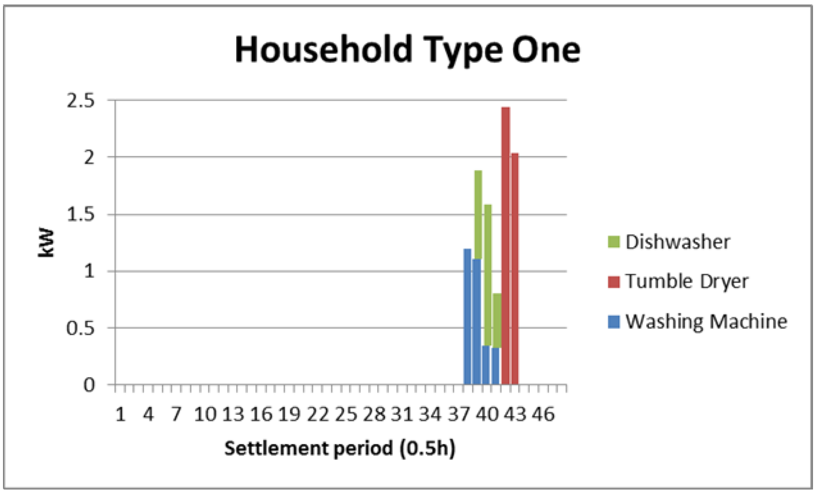


Figure 6-2 Flexible load profiles for household type one

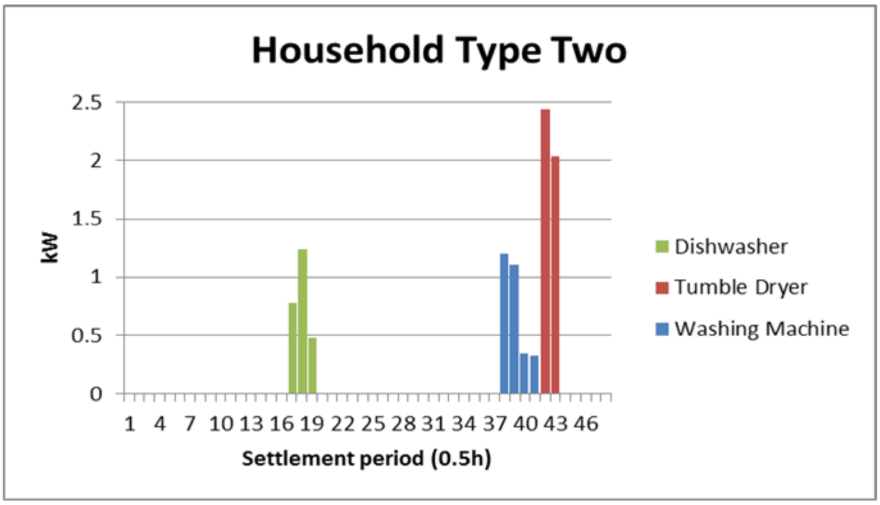


Figure 6-3 Flexible load profiles for household type two

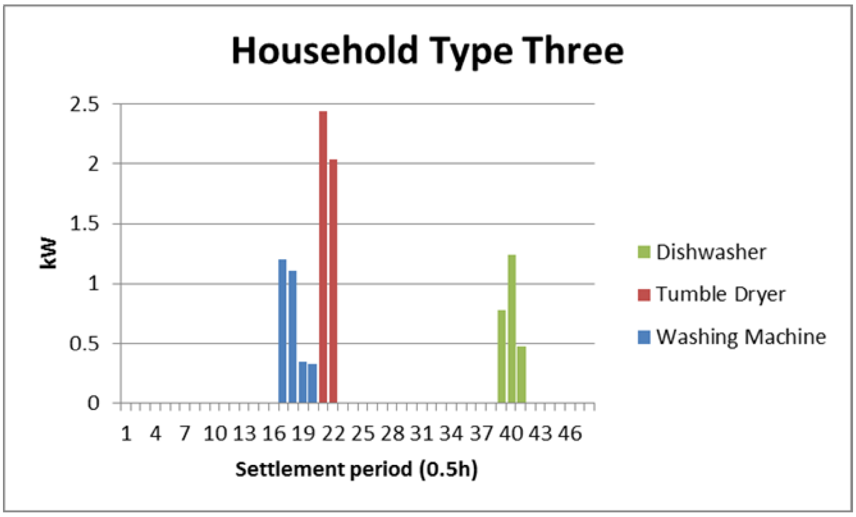


Figure 6-4 Flexible load profiles for household type three

6.4 Flexible Load Shifting Algorithm

For consumers in domestic sector, tariffs with half-hourly varied prices could hardly guide the DSR effectively. Therefore, the developed TOU tariffs in Chapter 3 with three-block pricing pattern are chosen to trigger DSR. Eight scenarios which are classified by season and day type will still be kept in the application of TOU tariffs.

Based on the eight TOU tariffs developed for weekdays and weekends in four seasons, the periods for accommodating shifted loads are achieved by the following steps:

i) Determine potential periods to accommodate shifted loads driven by price. The results are the off-peak periods in the employed TOU tariffs.

ii) Determine the expected start times of wet appliances to realise effective load shifting, considering customers' daily life habits and energy price variation. For every off-peak period during the daytime, its duration should be compared with the wash/dry cycle of each wet appliance. If the off-peak period lasts longer, the start time of the off-peak period is just set as the expected start time of the wet appliance. Otherwise, the flexible load has to be shifted to the next off-peak period.

Within a day, the longest off-peak period lasts from late evening to early morning. If wet appliances can start no later than midnight, these operations are considered feasible. Therefore, for general wet appliances, the proposed start times are defined as 12am if the beginning of the longest off-peak period in a TOU tariff is later than midnight. Otherwise, the start times of the wet appliances will be the beginning time point of the overnight off-peak period.

The running of washing machines and dryers needs a special attention in load modelling. It can be observed that dryers usually run after washing machines according to Figures 6-2, 6-3 and 6-4. Therefore, washing machines should be run early enough to guarantee the start times of dryers are before 12am. Meanwhile, the off-peak period before midnight is expected to be fully utilized for running washing machines.

iii) to determine the periods to fill the moved demands. For wet appliances, the proposed periods for shifting can be set from the expected start time of a wet appliance to the end of a running cycle. For customers who sleep late or get up early, the load shifting can be more flexible.

The detailed process of determining the periods to accommodate moved demands is shown in the flowchart in Figure 6-5.

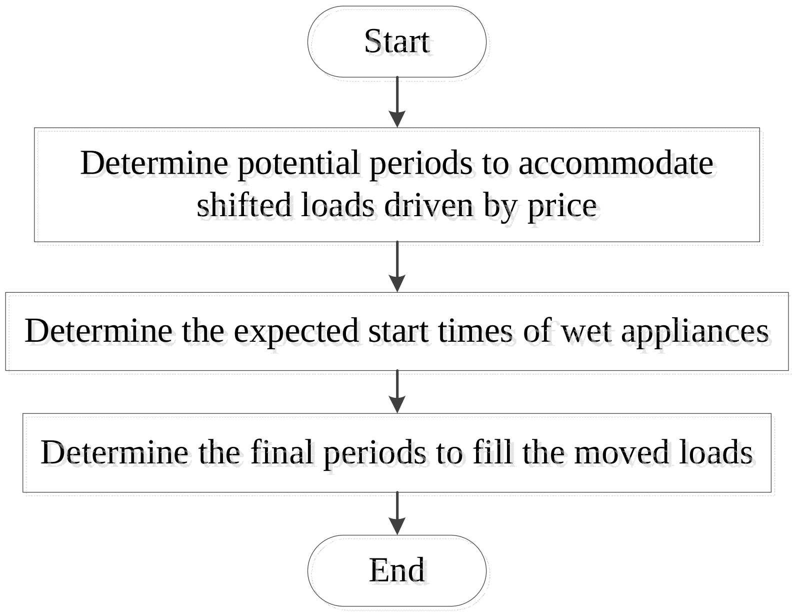


Figure 6-5 Flowchart of the final period determination to accommodate moved demands

6.5 Benefit Quantification

When customers change their energy consumption by shifting wet appliances in response to smart variable tariffs, the financial cost savings in electricity bills are quantified from a typical day to a whole year.

6.5.1 Daily Benefit Quantification

For the i^{th} type of appliance in the j^{th} day type, the financial cost over a distribution network is obtained by

$$C_{old,i\_j} = \sum_{n=1}^{3} \mathbf{E} \cdot \mathbf{L}_{h\_old,i\_j,n} \cdot t \cdot p_{i\_j,n} \cdot o_i \cdot N \tag{6-1}$$

where $\boldsymbol{E}$ stands for a 1×48 price matrix, which represents the TOU prices over a settlement day. $\boldsymbol{L}_{h\_old,i\_j,n}$ is the daily demand profile of the i^{th} type of appliance in the j^{th} scenario for the n^{th} kind of household. It can be represented by a 48×1 matrix, containing half-hourly household demand of a day. t is the length of each settlement period. For the n^{th} type of households, its percentage is $p_{i\_j,n}$. o represents the appliance ownership level and N is the household number in a distribution system.

Similarly, after flexible load shifting, the new cost is

$$C_{new,i\_j} = \sum_{n=1}^{3} \mathbf{E} \cdot \mathbf{L}_{h\_new,i\_j,n} \cdot t \cdot p_{i\_j,n} \cdot o_i \cdot N \tag{6-2}$$

Where $L_{h\_new,i\_j,n}$ is the new daily demand profile of the i^{th} type of appliance in the j^{th} scenario for the n^{th} kind of household after flexible load shifting.

The daily benefit in terms of financial cost reduction for each type of appliance is achieved by

$$B_{i\_j} = C_{new,i\_j} - C_{old,i\_j} \tag{6-3}$$

6.5.2 Annual Benefit Quantification

The daily benefit is regarded as the benefits from running a wash/dry cycle. Under any one of the eight scenarios, the running cycles per year is

$$cy_{i\_j} = \frac{D_{annual,i}}{D_i} \cdot \frac{d_j}{d_{annual,j}} \tag{6-4}$$

Where $D_{annual,i}$ represents the annual electricity consumption of the i^{th} appliance and D_i stands for its energy consumption for running a cycle. d_j is the number of days in the j^{th} scenario and $d_{annual,j}$ is the number of day in a calendar year.

Therefore, when wet appliances are shifted, the annual benefits $B_{annual,be}$ can be calculated by

$$B_{annual,be} = \sum_{j=1}^{8} \sum_{i=1}^{3} B_{i\_j} \cdot cy_{i\_j} \tag{6-5}$$

The benefit for each household is evaluated as

$$B_{annual,be,h} = \frac{B_{annual,be}}{N} \tag{6-6}$$

6.6 Cooperation with Energy Storage

The benefits from household demand shifting have been quantified in Section 6.5. However, the benefit from DSR could be extended by shifting inflexible loads through charging/discharging storage batteries. Besides, the whole-system benefit from DSR triggered by energy storage will be compared with that driven by household demand shifting as benefit evaluation from technical and social sides.

6.6.1 Benefit Comparison with Energy Storage

The effect of DSR enabled by household demand shifting is firstly compared with that enabled by storage battery usage. The equivalent capacity of battery that could achieve the same benefit as flexible load shifting is then quantified for each household. It aims to associate the DSR from social solution to that from storage solution.

The household benefit from shifting household demand can be obtained from (6-6), so the following task is to evaluate the benefit from DSR facilitated by energy storage. As there are three price steps in the developed TOU tariffs, off-peak periods are defined as the periods for battery charging. In contrast, the batteries are discharged during shoulder periods in summer and peak periods in other seasons. In these charging/discharging periods, it is assumed that battery charging/discharging power is constant and there is only one charging cycle within a settlement day. Following this principle, the annual financial benefits obtained from using per kWh storage can be approximated by

$$B_{st,un} = \sum_{j=1}^{8} \mathbf{E} \cdot (\mathbf{L}_{st,dis,j} - \mathbf{L}_{st,ch,j}) \cdot t \cdot d_j \tag{6-7}$$

Where $\boldsymbol{L}_{st,dis,j}$ and $\boldsymbol{L}_{st,ch,j}$ are 48×1 matrixes, representing half-hourly charging and discharging demand stemmed from a unit storage in the j^{th} scenario.

Once the annual benefit from using a 1 kWh storage battery is obtained, it could be compared with that from shifting household demand. The quotient of annual household benefit from flexible load shifting and that from using per kWh storage is defined as the equivalent storage capacity, which can lead to the same benefit from shifting flexible appliances. It is denoted by E_{qst}, and expressed as

$$Eq_{st} = \frac{B_{annual,be,h}}{B_{st,un}} \tag{6-8}$$

6.6.2 Cooperation with Energy Storage

In Section 6.6.1, the benefits from flexible load shifting have been compared with the impact of DSR enabled by energy storage on financial cost saving. Therefore, the investigated could be extended to benefit improvement when both energy storage and household demand shifting contribute to effective DSR.

The benefit from the DSR facilitated by their cooperation is estimated approximately by adding the benefits from the two sources together. The consequential total benefit for a household is

$$B_{annual,both,h} = B_{annual,be,h} + B_{st,un} \cdot Ca \tag{6-9}$$

Where $B_{annual,both,h}$ is the annual household benefit from the proposed cooperation. Ca represents the capacity of an employed battery for a household. Accordingly, annual whole-system benefit is estimated by

$$B_{annual,both} = B_{annual,both,h} \cdot N \tag{6-10}$$

Where $B_{annual,both}$ is the total cost saving in the test system.

6.7 Case Study

6.7.1 Test Network

In order to test the proposed methodology on a practical system, the LV network in Illminister Avenue is chosen for the case study, given in Figure 6-6 [90]. The parameters of the test network have been presented in Chapter 4. The TOU tariffs selected for load shifting are the results achieved from equal interval grouping method which is described in Chapter 3.

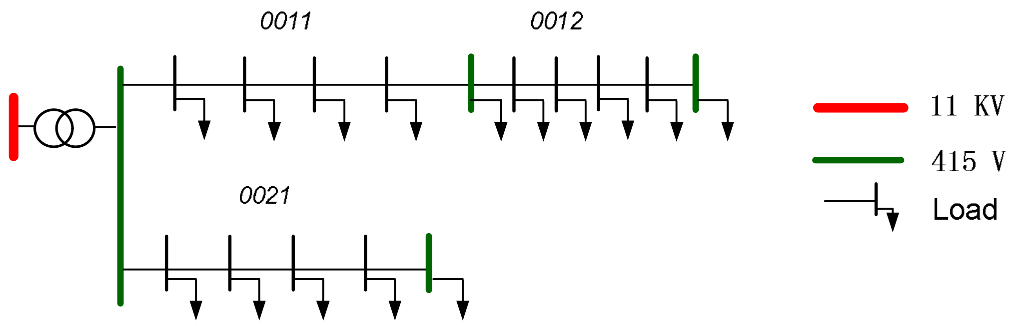


Figure 6-6 Layout of a LV network in Illminster Avenue

The wet appliance ownership levels in the UK collected from National Statistic [124] is shown in the fourth column of Table 6-1. They are used to represent the ownership levels in the test system. Besides, for each type of appliance, the energy consumption over a cycle and over a year are summarised in the second and third columns of Table 6-1.

Table 6-1 Wet appliances in modelling and related parameters

	Energy consumption per cycle (kWh)	Household electricity consumption in UK (kWh/year)	Ownership level (%)
Washing machine	1.49	205	96
Tumble dryer	2.24	427	57
Dishwasher	1.25	306	40

6.7.2 Test Results

1. Evaluation of household demand shifting

Following the benefit quantification process, the annual benefit achieved from shifting flexible loads can reach £13,750 in Illminster Avenue. If it is averaged among grid connected households, the financial cost saving is £53.50 per dwelling.

The annual benefit obtained from per kWh storage battery usage in this case is £37.84. If a storage battery is expected to generate the same benefit of £53.50, its equivalent capacity is evaluated as 1.41 kWh. The annual benefit assessments for DSRs from shifting household demand and applying storage batteries are listed in

Table 6-2.

Table 6-2 Annual benefit assessment for DSR enabled by household demand shifting and storage application

	Per unit household/storage benefit (£)	Equivalent storage capacity(kWh)
Household demand shifting	53.50	1.41
Per unit storage battery application	37.84	1

2. Cooperation between household demand shifting and storage

Similar to the case study carried out in Chapter 5, a 4.8 kWh in-home storage battery is assumed to be installed for each household connected to the test network. As shown in Table 6-3, the benefit from DSR enabled by a distributed battery is as high as £181.63 over a year. Accordingly, annual benefit can be increased to £235.13 if both household demand shifting and storage implementation are conducted. The result from demonstration shows that there will be a financial saving of £60,408 in the whole system of Illminister Avenue if the DSRs from technical and social sides are realized simultaneously.

Table 6-3 Annual benefit assessment for DSR enabled by the cooperation between household demand shifting and storage application

	Household benefit (£)	Whole-system benefit (£)
Household demand shifting	53.50	13,750
Real storage battery application	181.63	46,679
Cooperation between household demand shifting and battery application	235.13	60,428

6.8 Chapter Summary

This chapter evaluates the benefits from DSRs enabled by social solution. The benefits from shifting flexible loads to off-peak periods are assessed over a year at household and system levels, in respect to smart variable tariffs with TOU patterns. The performance of DSR facilitated by shifting wet appliances is compared with that enabled by energy storage to understand their impact on total cost savings. In order to achieve the same benefit as the household demand shifting in the case study, 1.14 kWh is considered as the equivalent capacity of storage battery for each household. If the combination of battery usage and household demand shifting can be realised to trigger DSR, annual household benefit can reach £235.13.

Chapter 7

Conclusion

THIS chapter draws the conclusion to the thesis by outlining the major contributions and key findings based on the proposed methodology.

Currently, the majority of the residential customers in GB purchase their electricity with flat-rate tariffs. The regulated fixed rates are unable to encourage customers to shift their load with the change of balance between demand and supply. In order to serve the purpose of load shifting, innovative tariff structures are needed to enable DSR.

Smart tariff, as an incentive to trigger DSR, plays a critical role in energy management under smart grid environment. Load shifting in response to the appropriate pricing signals will lead to energy cost savings and network investment savings. In this thesis, the investigations of smart tariff designs and applications focus on four aspects:

i) Smart variable tariffs are designed for a conventional high-carbon system dominated by controllable fossil generation where energy pressure and network pressure are in synchronisation. Thus, peak demand reduction will automatically reduce energy price and vice versa. The proposed RTP tariffs are developed by statistically tracking dynamic energy price variations, and the RTP prices are categorised to form TOU patterns that capture the most significant price variations without compromising too much accuracy in total energy revenue from customers.

ii) Smart variable tariffs are applied in a future low carbon system where wholesale energy pressure and network pressure may not be conforming, i.e. the system might be over stretched when renewable generation is abundant. If the DSR is only mobilised by smart variable tariffs with the aim to reduce energy cost, network constraint could not be mitigated under this condition. A new concept is developed in this thesis to allow energy storage to be shared between customers and DNOs to respond to conflicting energy price and network conditions. Two shared ownerships of battery utilization are implemented in this thesis. One is fixed share between customers and DNOs regardless of network conditions, and the other is dynamic share that DNO ownership of storage changes with network condition.

iii) Smart variable tariffs are also utilized to manage energy consumption when home area energy storage is intergraded with distributed generation. In this scenario, the dynamic share of battery is realized by an innovative methodology, defined as “charging envelope”. Customers can respond to the variable tariffs to take advantage of lower energy prices, and DNOs are able to communicate with batteries through the proposed charging envelopes for network management. With the cooperation between charging envelopes and smart variable tariffs, the benefits in terms of energy cost reduction and network cost saving are eventually converted into per unit cost reduction in energy bill so that customers can understand the benefit clearly. The unit cost reduction is defined as smart fixed tariff in this work.

iv) The benefit from household demand shifting, such as shifting wet appliances, in the presence of smart tariffs is evaluated. The value of the demand shifting is quantified as an equivalent storage capacity for the investigation of complementarity between technical and social interventions.

In detail, the work in this thesis carried out from four perspectives:

Smart Variable Tariff Design to Reflect Wholesale Energy Cost in Conventional High-Carbon Systems

Under high-carbon generation environment where peak demand is generally met by expensive generation plants, smart variable tariffs are designed based on energy price variation, relying on the form of RTP and TOU. The responses to these tariffs are therefore not only capable of reducing energy cost, but also effective in peak shaving.

Firstly, RTP tariffs are developed based on annual energy price variation. Then, the major contributions to these variable tariff designs lie in two novel approaches to convert RTP tariffs to TOU tariffs for implementing DSRs. They use equal interval grouping method and hierarchical clustering method respectively. The tariffs developed by each approach contain eight scenarios, i.e. weekdays and weekends of four seasons, to reflect diversity of tariffs within a year.

Even though both of these two approaches are able to successfully develop TOU tariffs from RTP forms, each approach has its own characteristics and lays emphasis on different aspects:

- The TOU tariffs achieved by statistically grouping settlement periods of RTP tariffs consider annual price variation as a whole. The time windows can be determined without the perturbation of critical peak or trough energy prices.

- The TOU tariffs obtained by clustering methods place the settlement periods with similar prices in RTP into a cluster. Therefore, these TOU price profiles are closer to the shapes of original RTPs. Besides, the number of clusters is optimized considering both accuracy and feasibility of implementation.

In the results of smart variable tariff designs, the RTP tariffs developed for different reasons vary considerably. Peak prices generally occur in winter, and the prices in summer are much flatter. The peak price rate in summer weekday is 76% of that in winter weekday, and the value of peak price in summer weekend is only 66% of the highest price in winter weekend. Moreover, the RTP prices in weekends are higher than those in weekdays. It is mainly due to the inaccuracy of load estimation at weekends.

The TOU results achieved from equal interval grouping and hierarchical clustering methods shows that:

- The RTPs which reflect energy price variation can be represented by TOUs with no more than three price steps and eight time intervals within a day through the two proposed approaches. The off-peak periods of TOU tariffs usually between midnight and 6am in the morning and the peak is either in the early evening or late morning.

- In the TOU results obtained by the equal interval grouping method, it can be observed that the off-peak price rates and durations for weekdays are roughly the same. Then, two time intervals are considered as peak periods in a typical spring weekday, but none of the settlement periods in a summer weekday are assigned to peak categories. Even though both winter and autumn have a time interval for peak price, the degrees of price levels and durations in winter are much higher than the degrees in autumn. Compared with the TOU tariffs designed for weekdays, the TOUs for weekends have longer peak periods. Besides, two peak periods which occur in the morning and evening respectively are designed for all typical weekends except in summer.

- In the TOU results obtained by the hierarchical clustering method, the durations of peak periods in winter are shown not as long as those in other seasons although prices in winter weekdays and weekends are generally higher in the original RTP tariffs. The reason for the shorter peak periods in winter is that the settlement periods with critical high prices in winter RTP tariffs mainly contribute to peak period formation. Besides, the price rates of the eight scenarios vary dramatically from one to another, no matter in peak, shoulder or off-peak period.

Active DSR enabled by Shared Energy Storage and Smart Variable Tariffs in Low Carbon Systems

The smart variable tariffs achieved from energy price variation can be applied to trigger DSR in conventional high carbon systems. However, in low carbon systems, network pressure is not always synchronous with energy price pressure. For the benefits from wholesale energy cost saving and distribution network investment deferral, distributed storage batteries are employed with joint ownership between customers and system operators, responding to RTP tariffs, which reflect energy price variation, and network condition respectively. The energy storage capacity controlled by customers takes the periods with the lowest energy prices to charge and the periods with highest energy prices to discharge. The remaining energy storage capacity operated by network operators is expected to shave peak demand for network pressure mitigation. It will be discharged during the period with heavy load and charged in off-peak period to store energy.

Compared to traditional work on using storage battery in response to energy price signals, the innovations in this part are represented by:

- A novel concept of sharing the storage battery ownership between customers and network operators is proposed for responding to wholesale energy price variations and network conditions.

- The fixed and dynamic operation scheme of the storage with shared ownership is developed for appropriate battery operation by end users and system operators to meet the needs of reducing energy costs and network investment costs.

- A sensitivity analysis is conducted to investigate the impact of the variation of energy storage capacity share on the benefits under prefixed operation mode of storage.

- New quantification methodologies are introduced to evaluate the benefits that the shared energy storage can bring forward over a year in terms of savings in energy cost and network investment under both prefixed operation model and dynamic operation model.

Through demonstrating the proposed method on practical networks, it can be observed that battery capacity share enables up to 8% energy cost saving and 17% reductions on peak demand for each household in a typical day. When the benefit quantification is conducted over a whole year, annual financial benefits in Illminister Avenue network vary from £1,092 to £1,202 under different fixed dispatch scenarios of storage battery. For Marwoord Road distribution system, the maximum benefit from fixed storage dispatch can be £8,093. The implementation of dynamic dispatch is capable of increasing annual cost savings to £1,276 and £9,026 respectively.

Therefore, the key finds are presented from the following aspects:

- On a daily basis, the average capacity share between customers and DNOs can lead to bigger peak shaving. However, energy cost saving in this scenario is always less than that in traditional scenario where storage capacity is fully employed to respond energy prices as less proportion of energy storage is controlled by customers.

- When the demonstration is extended to a whole year, different percentages of storage capacity division between customers and operators can lead to totally different electricity bill saving and shaved peak demand. Particularly, the operation based on joint ownership can produce more benefits in terms of total cost savings for highly utilised networks. Under different network conditions, appropriate prefixed dispatch cases can be selected for more benefits.

  i) For low utilised networks, more proportion of energy storage capacity should be allocated to respond to energy prices;

  ii) For highly utilised networks, more storage capacity should be reserved to respond to network conditions.

- When the capacity share is dynamic throughout a year, the annual total benefit is higher than any pre-fixed option and it is therefore considered to be the most effective approach for operating energy storage with joint ownership to facilitate DSR.

Enhanced Battery Management and Smart Tariff Improvement for DSR and Distributed Generation Utilization

The energy storage with joint ownership has been proved to be effective in energy price pressure and network pressure mitigations. However, this method focuses on the management of energy from conventional main grid and the issues from distributed generation usage are not considered. Moreover, the shared battery capacity operated by customers or DNOs is expected to be changeable within a day to improve its efficiency in network pressure mitigation and energy cost minimization.

Therefore, an innovative concept of “charging envelope” is proposed as an improvement of battery share. The household energy management system utilises the innovative charging envelopes, coupled with smart variable tariffs to enable PV generation to connect to LV networks more efficiently when the penetration level of PV reaches 100%.

Basically, if there is no congestion in a distribution system, charging envelopes are developed to take advantage of PV generation together with reducing system peak. However, when network congestions occur in a LV network, the charging envelopes designed for overloading and over generation conditions show that:

- Under overloading conditions, a portion of storage capacity will be reserved for discharging during congested period. The reservation amount, which is indicated by a decline on upper boundary of charging envelope, is directly proportional to overloading degree and duration.

- Under over generation conditions, an increasing slope on lower boundary of charging envelope represents the reserved storage capacity for battery charging to mitigate network pressure. The reserved capacity is in proportion to over generation degree and duration.

Optimised battery operation is conducted via the correlation between charging envelopes and smart variable tariffs. Based on the demonstration results shown as the changes of system load profiles, it can be found that the annual peak demand in the test distribution system of Illminister Avenue is reduced from 0.345 MW to 0.302 MW, with a reduction of 12.4%. Along with the peak demand shaving, the energy cost saving in purchasing electricity from main grid can reach up to £136.17 per day. The annual benefit for the whole test system is calculated as £66,483.

In charging envelope implementation, TOU tariffs are selected as the smart variable tariffs to drive DSR from storage battery. As it is noted that such tariffs are difficult for customers to understand, the total benefit obtained from PV generation and battery operation is expressed to customers as a discount on a fixed tariff, which could be as much as 14% reduction of the original price. The tariff with per unit cost reduction can be regarded as a new form of smart tariff, defined as smart fixed tariff.

Extending Storage Solution to Social Solution for Effective DSR

Household demand shifting is guided in response to smart variable tariffs as well. With shifting flexible wet appliances, annual electricity cost saving can be as much as £54 for each household. This financial saving is considered as the benefit from social side.

However, in order to achieve the same cost saving target of £54 per household, the storage with the capacity of 1.14 kWh is needed to respond to the proposed smart variable tariffs. This equivalent capacity successfully links the performance of flexible load shifting to the response enabled by energy storage. Moreover, once the investigation of DSR is extended to the cooperation between a 4.8 kWh storage battery and household demand shifting, the annual household benefit can reach £235.

Chapter 8

Future Work

THIS chapter presents future work that can be done to improve the investigations of smart tariff designs and applications.

Alternative TOU Tariffs Application

The applications of TOU tariffs obtained by equal interval grouping method have been investigated in this thesis. In response to these TOUs, consequent DSRs are enabled by distributed energy storage and customer behaviour changes for energy cost reduction and peak demand shaving. However, the TOU tariffs achieved by hierarchical clustering method have not been tested to implement DSR. In future work, the benefit assessments of their applications are required to identify which TOU tariff design approach is more effective to trigger DSR. This identification can be considered as an important reference for smart tariff development in the GB electricity market.

Practical Individual Load Profile Implementation

In order to test the proposed energy management algorithms in domestic sector, generic GB aggregated unit load profiles proposed by Elexon is employed in this thesis to represent the demand variations of individual customers. However, if the energy management schemes are applied into practice, they may be inefficient for energy cost reduction and peak demand shaving due to a number of uncertain demand spikes in real load profiles. Therefore, a key task in the future is to investigate the impact of the proposed method on practical individual load profiles which are not smooth at all.

The further study also needs to focus on the benefit assessments in terms of wholesale energy cost saving and network investment saving to identify the feasibility of the proposed method in practical energy management. If there are large deviations between the demonstrated result with adopting practical individual load profiles and that with smoother aggregated unit profiles, the battery charging/discharging algorithms and charging envelope design processes need to be modified to accommodate to real situations.

Charging Envelope Improvement

The introduction of the “charging envelope” mainly focuses on the explanation of the concept and its operation method in response to smart variable tariffs in this thesis.

For enabling charging envelopes to accommodate more complex situations in real distribution network, they can be improved and modified in the future with the additional consideration from the following four perspectives:

- **Diversity of customers**: Instead of adopting similar household load profiles and the same size of storage batteries in test LV networks, diverse end users and storage battery capacities need to be taken into consideration. Therefore, a study in the future can be carried out to investigate charging envelope improvement based on diverse customers' contributions to network pressure relief and various battery operational costs.

- **PV generation uncertainty**: The PV generation amount over a day can be predicted more accurately by considering its uncertainty. Accordingly, the optimised the capacity reservation amount for PV charging in charging envelope design is required to accommodate complicated real weather conditions.

- **HV network congestion**: Not only network congestions at LV distribution level, but also the pressures in High Voltage (HV) networks are expected to be mitigated by implementing charging envelopes. Therefore, the charging envelopes can be modified to mitigate HV network pressure as well.

- **Three phase imbalance**: Three phase imbalance needs to be considered due to the possibility that PV penetration level is different in each phase. The imbalance may lead to the result of using different types of charging envelopes in different phases.

Smart Pricing and Energy Management Extended to Commercial Sector

The smart variable tariffs have been used to trigger DSR from domestic sector in this thesis and the consequential benefits are converted to the discount of per unit cost. Both the energy management scheme and the benefit quantification are associated with typical domestic load profiles. However, the load profiles in domestic sector and those in commercial sector are completely different, particularly in the duration of peak demand. Therefore, the proposed energy management scheme in which batteries are generally charged during daytime and then release energy in early evening is not suitable for commercial users. The energy management scheme for commercial customers may need to pay more attention to energy management cooperated with domestic users nearby. The electricity consumption for commercial usage in the daytime could be supported by the energy generated by household PV. In contrast, commercial users can export the energy they stored to domestic customers in the evening to reduce system peak demand. The energy management is expected to be cooperated between different sectors due to the fact that commercial demand peak, which generally occurs in daytime, is not in accordance with common whole-system peak that happens in the evening. When the energy management is conducted in commercial sector to take advantage of renewable generation, off-peak energy prices and effective network operation, the consequent financial benefits can be covered to unit price reduction in commercial electricity tariffs.

Appendix. A

A.1 Distance Changes with Number of Clusters

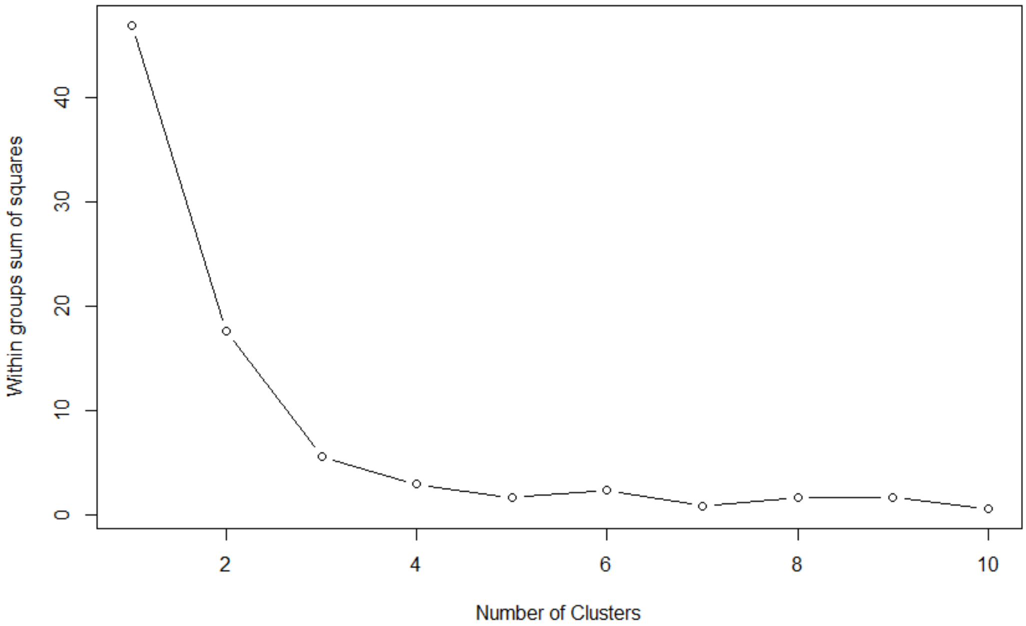


Figure. Appendix-1 Distance changes with number of clusters for winter weekday prices

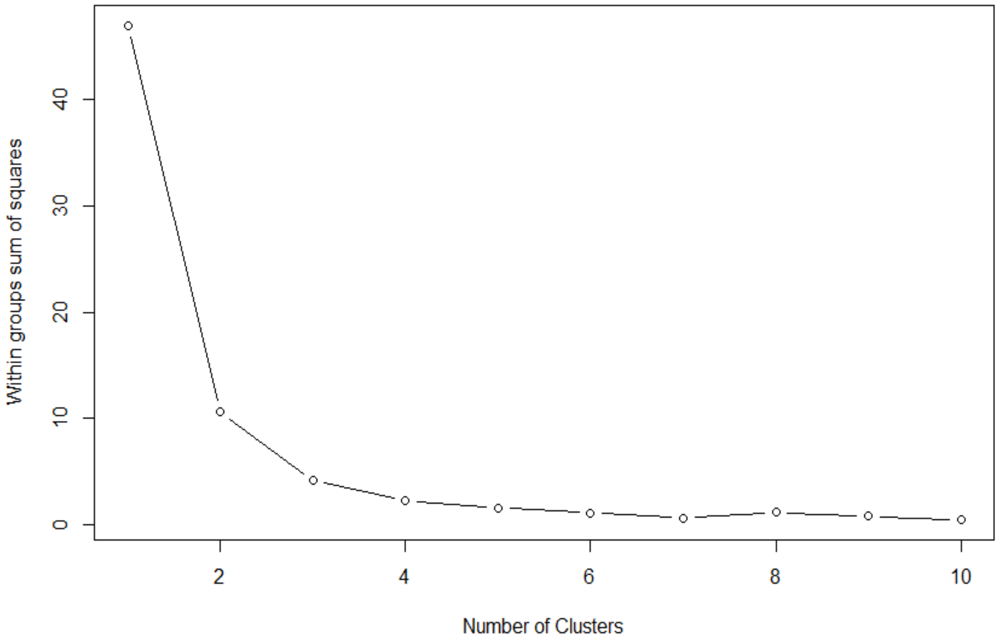


Figure. Appendix-2 Distance changes with number of clusters for spring weekday prices

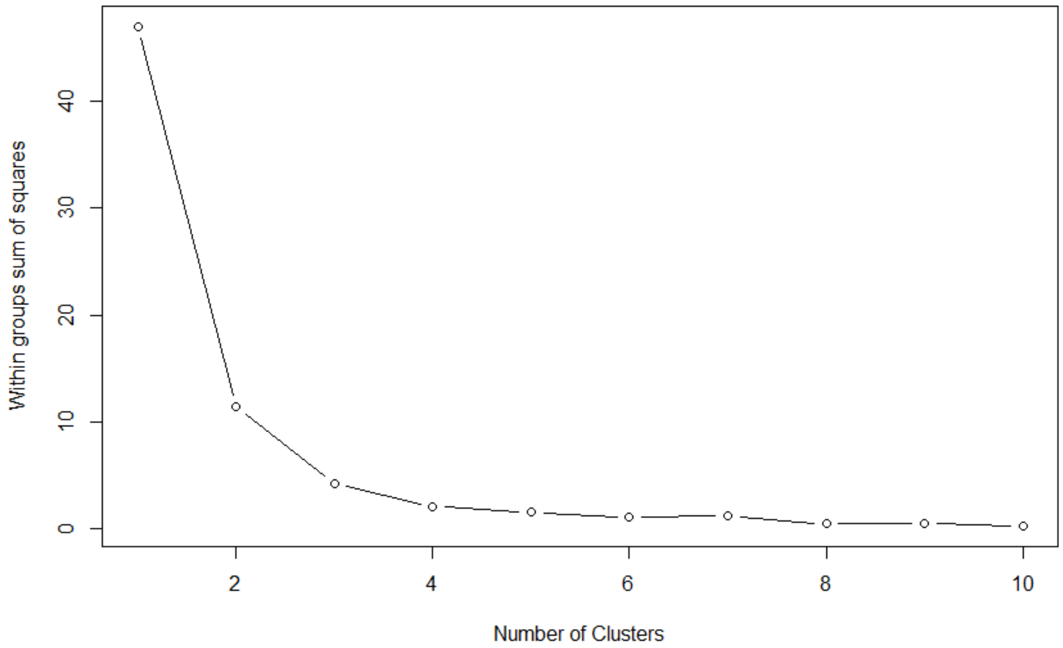


Figure. Appendix-3 Distance changes with number of clusters for summer weekday prices

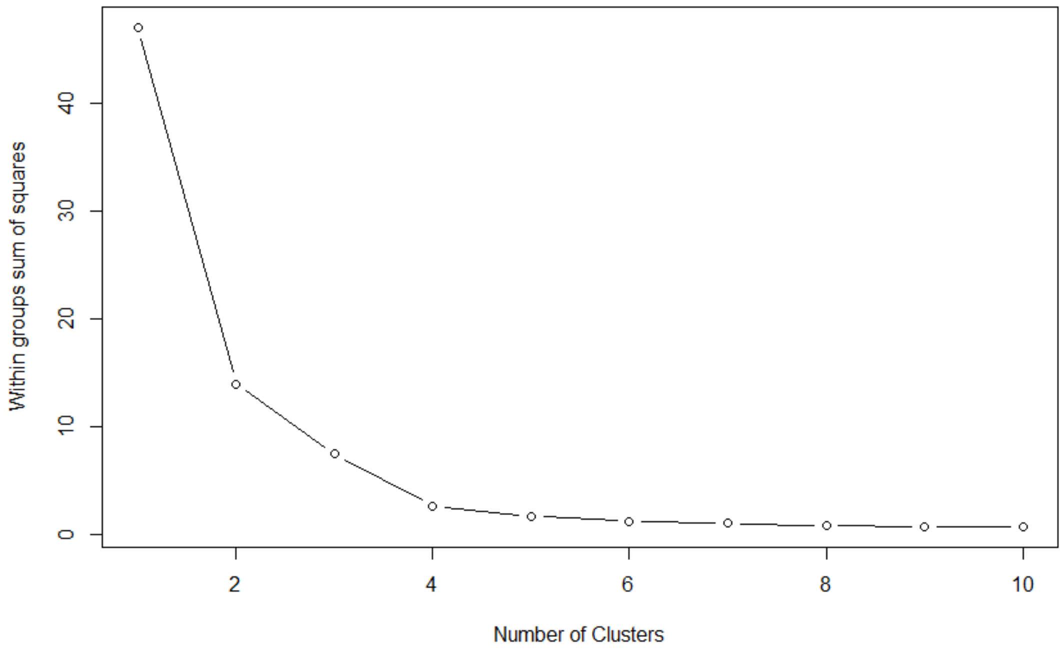


Figure. Appendix-4 Distance changes with number of clusters for autumn weekday prices

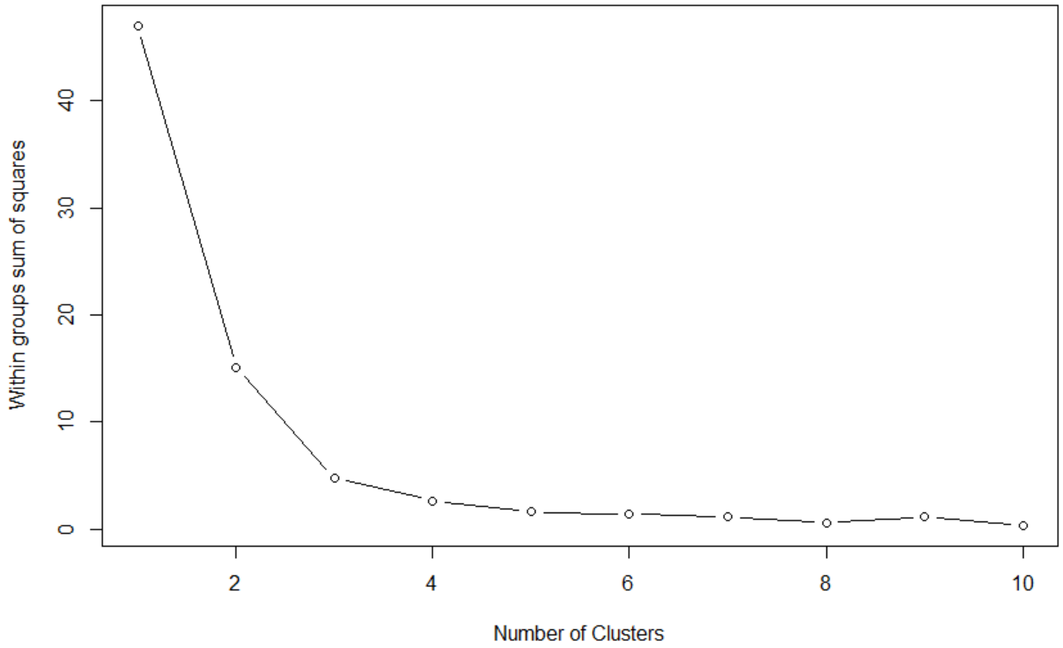


Figure. Appendix-5 Distance changes with number of clusters for winter weekend prices

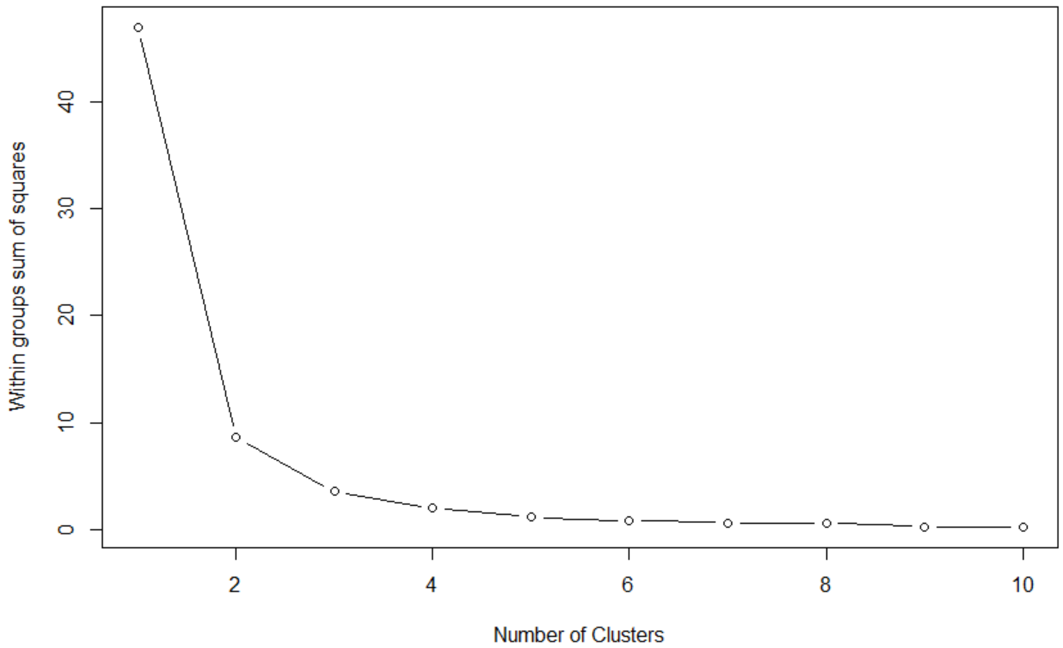


Figure. Appendix-6 Distance changes with number of clusters for spring weekend prices

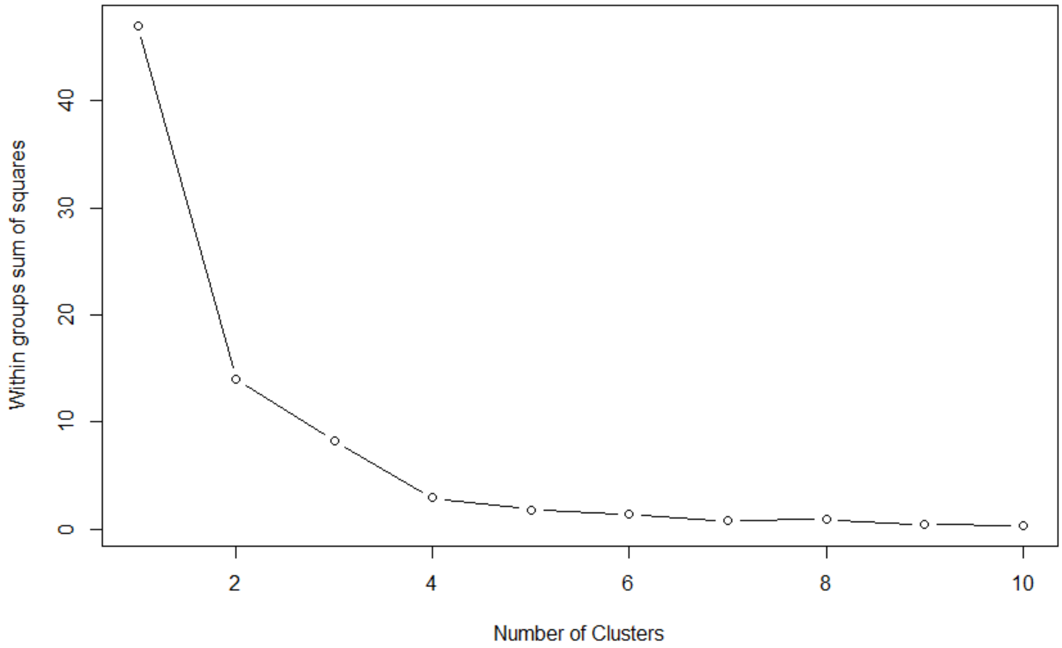


Figure. Appendix-7 Distance changes with number of clusters for summer weekend prices

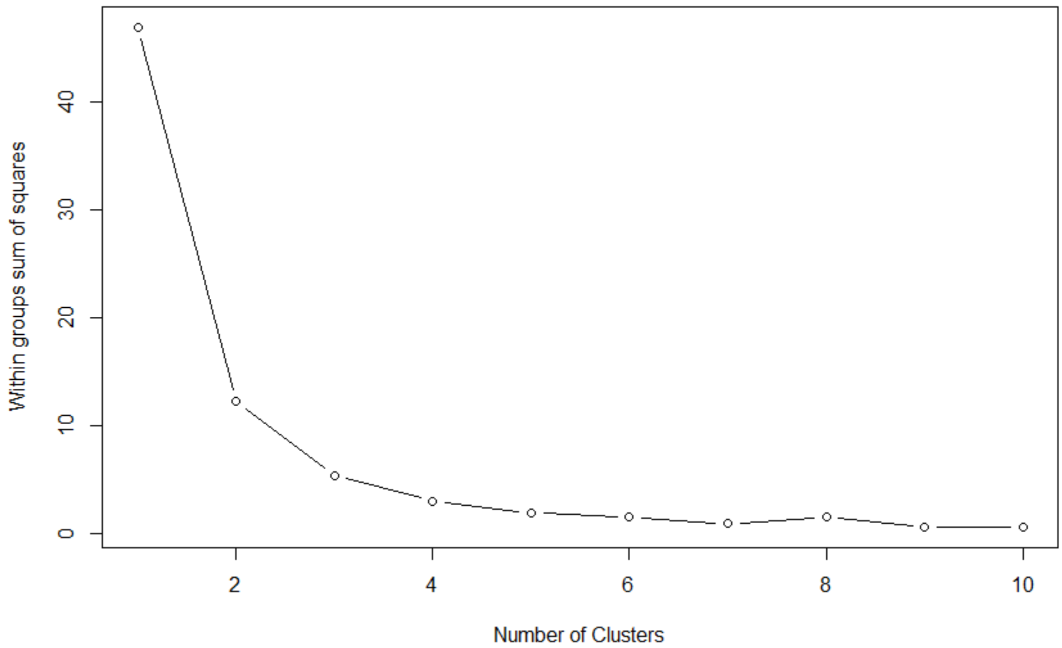


Figure. Appendix-8 Distance changes with number of clusters for autumn weekend prices

A.2 Cluster Tree Represented in Dendogram

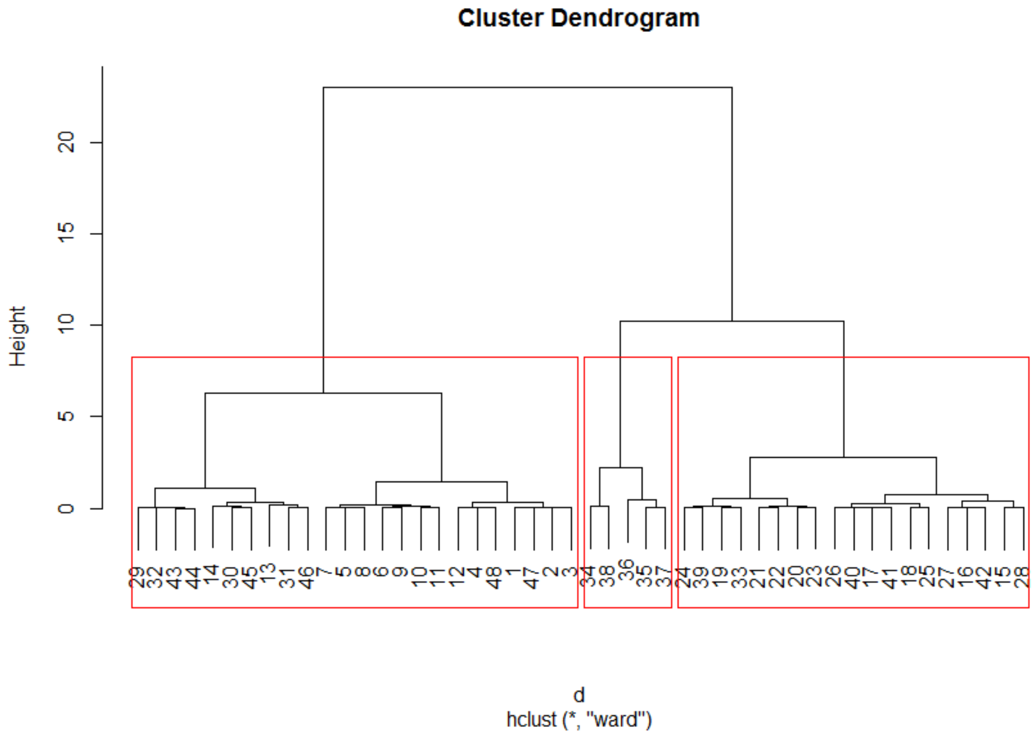


Figure. Appendix-9 Cluster tree for winter weekday prices

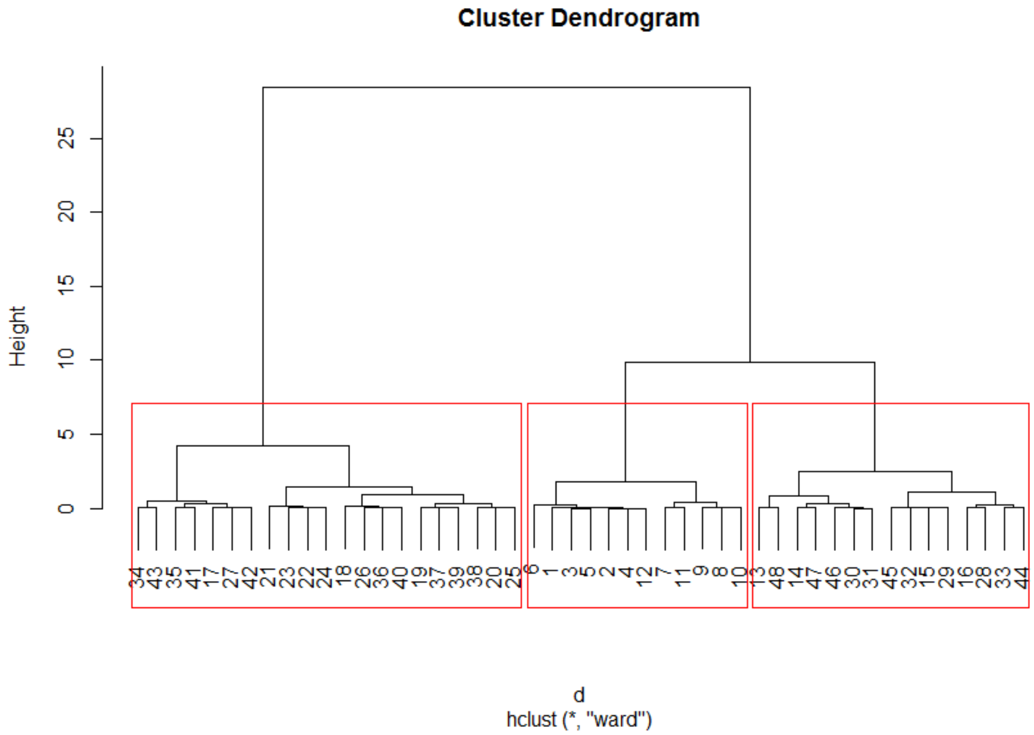


Figure. Appendix-10 Cluster tree for spring weekday prices

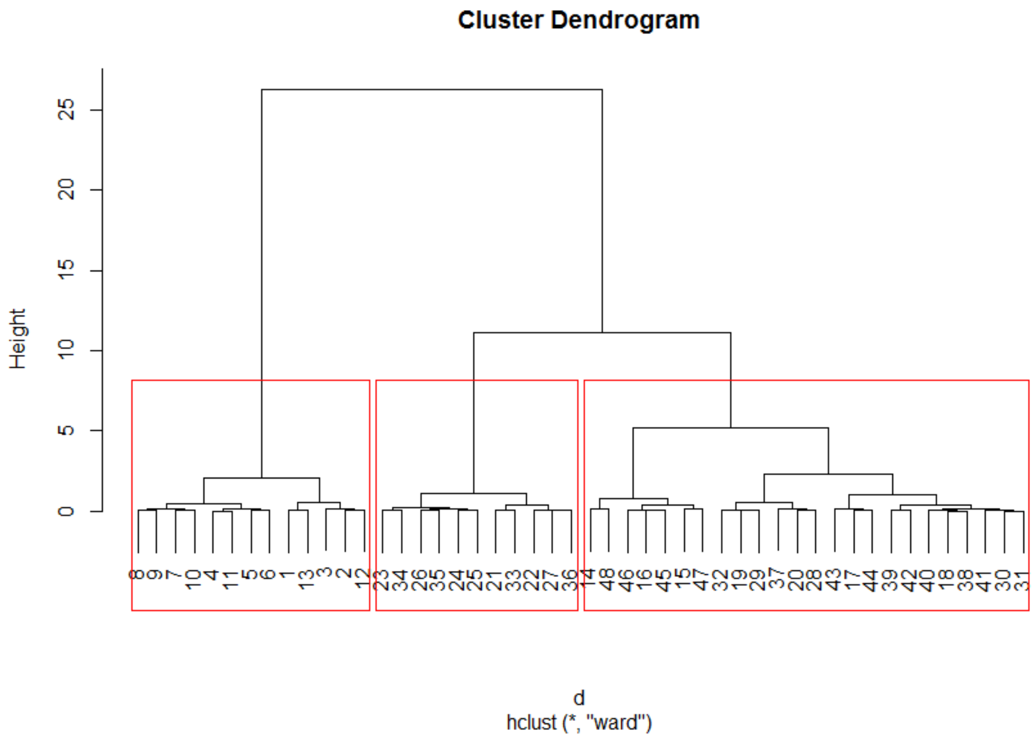


Figure. Appendix-11 Cluster tree for summer weekday prices

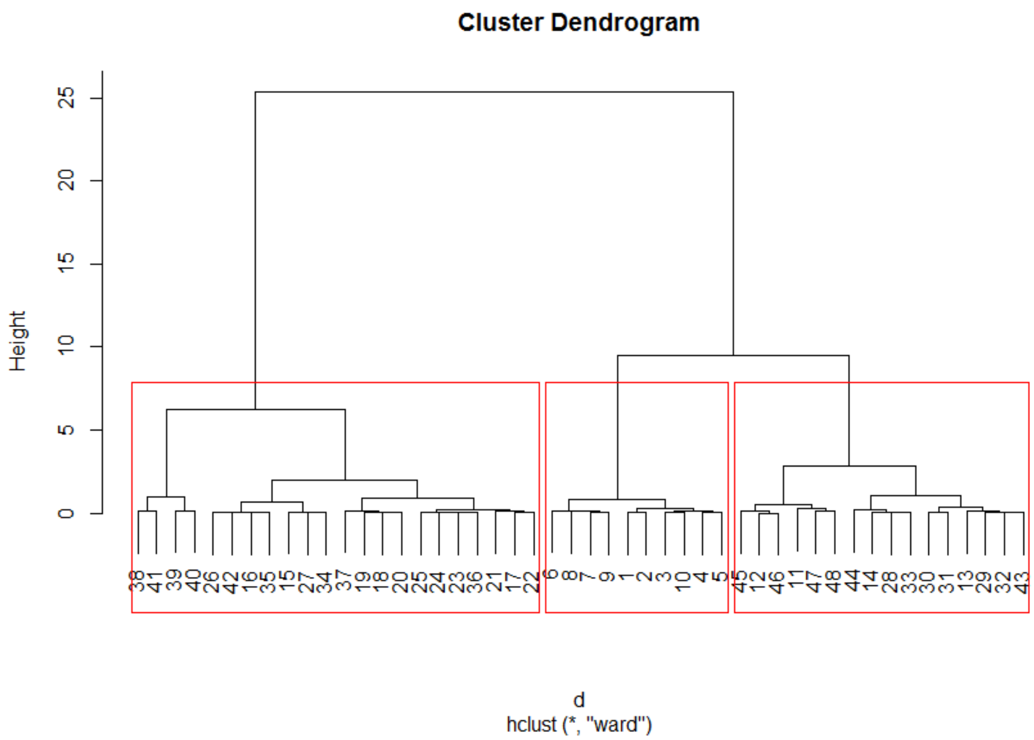


Figure. Appendix-12 Cluster tree for autumn weekday prices

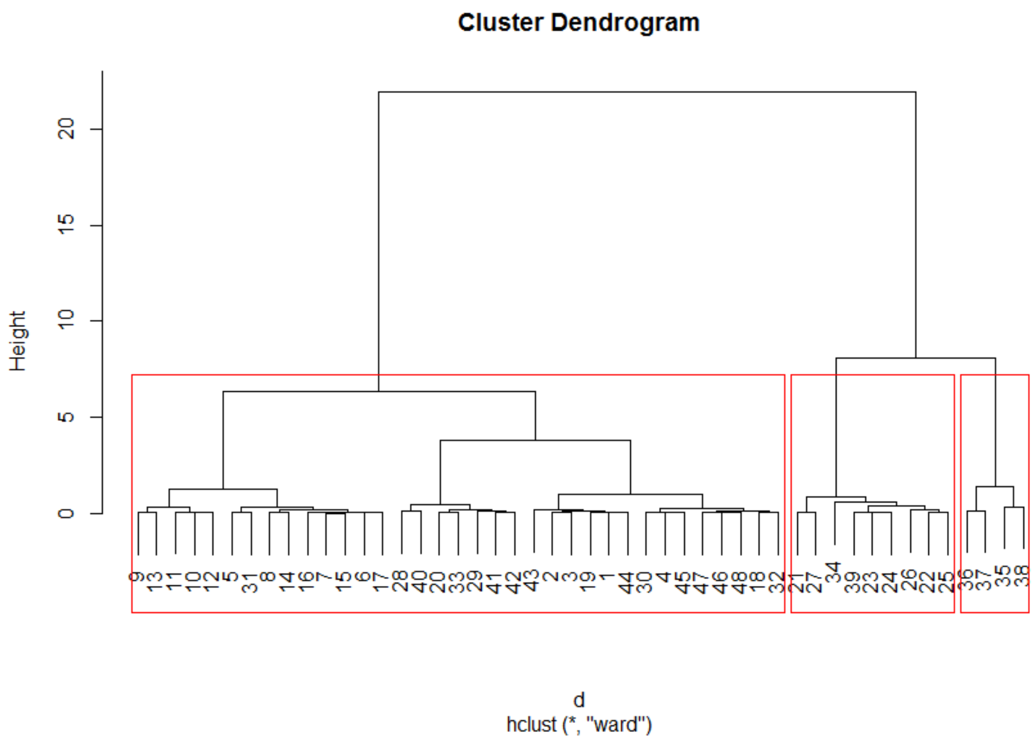


Figure. Appendix-13 Cluster tree for winter weekend prices

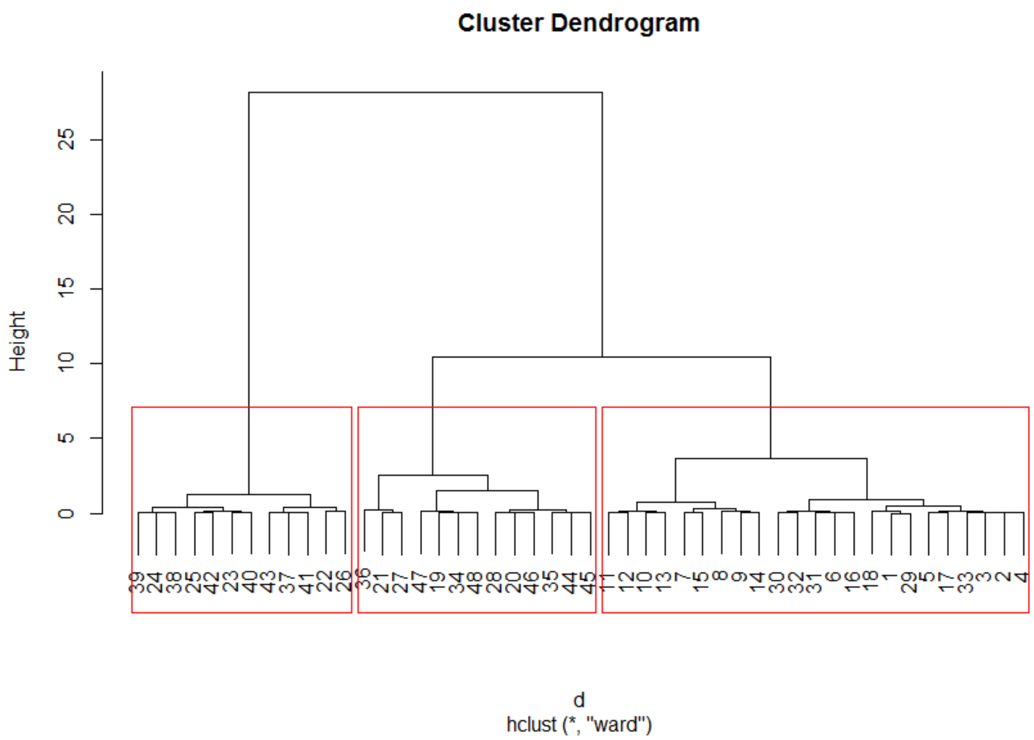


Figure. Appendix-14 Cluster tree for spring weekend prices

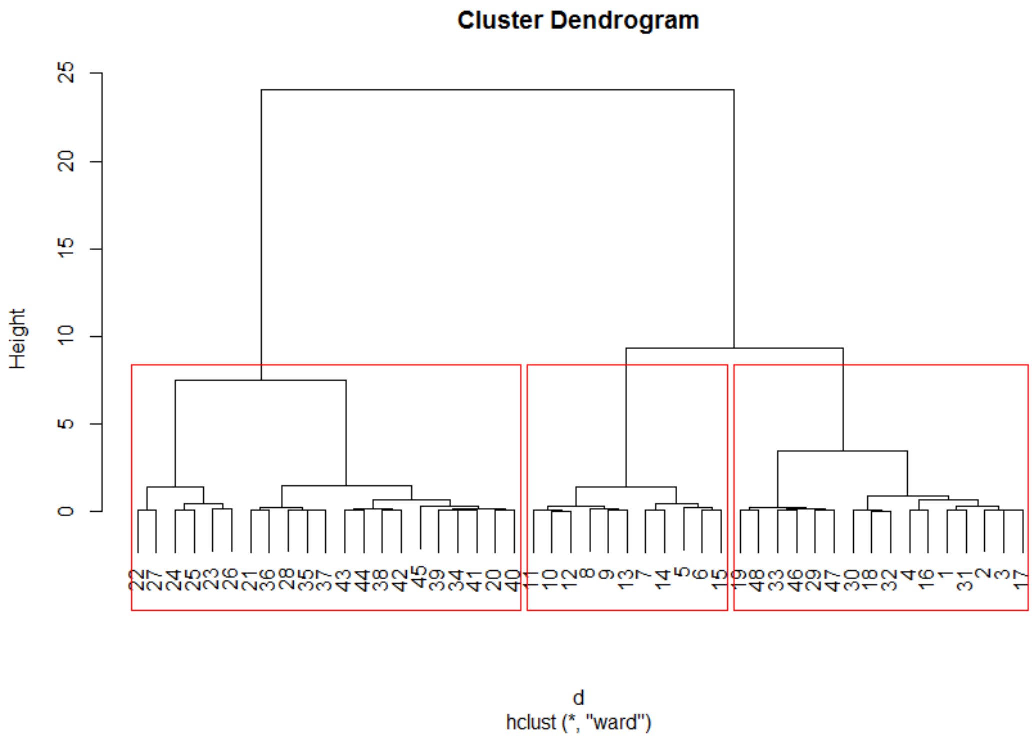


Figure. Appendix-15 Cluster tree for summer weekend prices

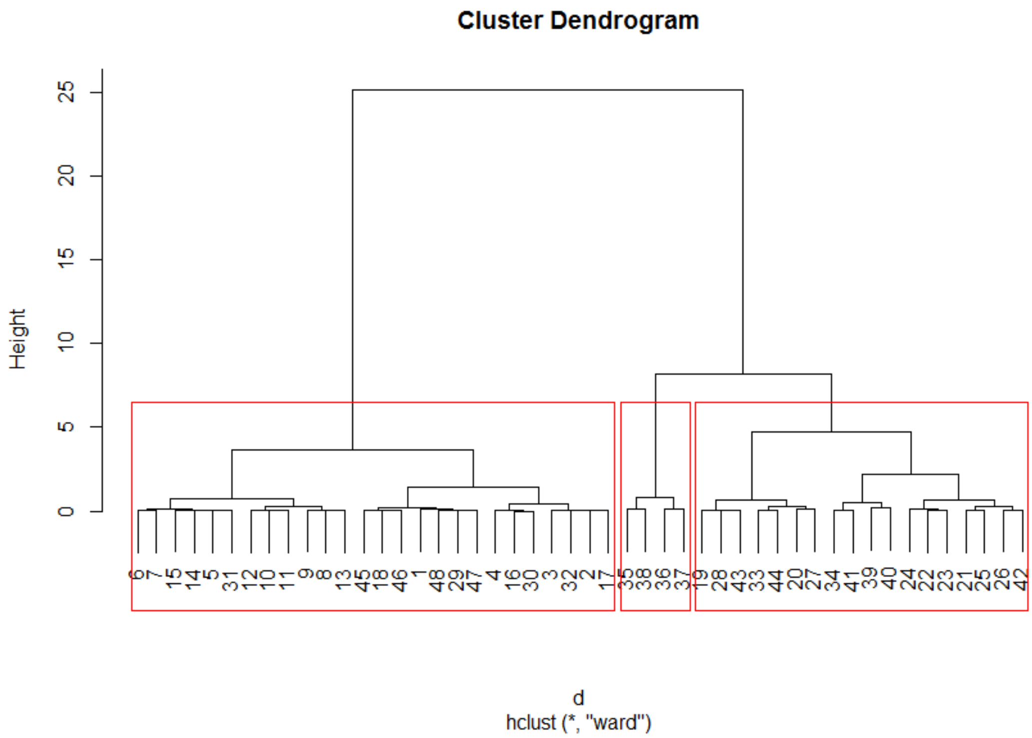


Figure. Appendix-16 Cluster tree for autumn weekend prices

Appendix. B

B.1 Typical Asset Cost

Note: due to confidential reason, the detailed date of the test system cannot be provided, but a list of typical asset cost is given in Table Appendix-1.

Table. Appendix-1 Unit costs for modelled asset replacement

Asset	Units	IP	FP	PB Power	IP - FP (%)
Services					
OHL - Service Replacement	#	0.40	0.40	0.70	0.0%
OHL - Cut-out Replacement	#	0.15	0.20	-	32.8%
UG - Service Replacement	#	1.00	1.01	0.93	1.3%
UG - Cut-out Replacement	#	0.16	0.16	-	4.7%
Cables					
LV Main (UG Plastic)	km	77.9	98.4	80.7	26.4%
6.6/11kV UG Cable	km	89.5	82.9	82.3	-7.4%
20kV UG Cable	km	89.5	82.9	167.9	-7.4%
HV Sub Cable	km	300.0	300.0	210.1	0.0%
33kV UG Cable	km	264.9	256.8	253.4	-3.1%
66kV UG Cable	km	300.0	300.0	455.4	0.0%
EHV Sub Cable	km	300.0	300.0	608.4	0.0%
132kV UG Cable	km	1091.9	1047.1	1031.0	-4.1%
132 kV Sub Cable	km	2167.0	1966.7	1216.8	-9.2%
Transformers					
6.6/11 kV Transformer (PM)	#	3.4	2.9	4.2	-15.1%
6.6/11 kV Transformer (GM)	#	14.0	13.2	13.3	-5.5%
20 kV Transformer (PM)	#	3.7	0.5	6.5	-86.4%
20 kV Transformer (GM)	#	12.3	14.4	16.4	17.1%
33 kV Transformer (PM)	#	5.8	7.9	5.8	36.0%
33 kV Transformer (GM)	#	399.8	377.9	519.6	-5.5%
66 kV Transformer	#	455.5	440.2	616.7	-3.4%
132 kV Transformer	#	1077.9	1018.7	1200.7	-5.5%
Switchgear					
LV Pillar (ID)	#	6.4	6.4	7.5	0.0%
LV Pillar (OD)	#	6.8	6.8	6.6	0.0%
LV Board (WM)	#	8.4	8.4	10.6	0.0%
6.6/11 kV CB (PM)	#	8.4	8.2	11.0	-2.6%
6.6/11 kV CB (GM) - Primary	#	58.7	51.8	31.8	-11.7%
6.6/11 kV CB (GM) - Secondary	#	11.7	11.2	10.4	-3.9%
6.6/11 kV Switch (PM)	#	4.1	2.5	7.5	-39.0%
6.6/11 kV Switch (GM)	#	8.2	7.0	8.9	-14.3%
6.6/11 kV RMU	#	12.0	13.0	13.8	8.0%
20 kV CB (PM)	#	8.4	8.0	13.8	-5.0%
20 kV CB (GM)	#	12.2	12.0	64.4	-1.4%
20 kV RMU	#	12.9	14.5	16.4	12.5%
33 KV CB (ID)	#	110.0	109.0	85.5	-0.9%
33 kV CB (OD)	#	83.7	50.1	60.2	-40.1%
33 kV RMU	#	259.5	259.5	31.8	0.0%
66 KV CB (ID & OD)	#	313.4	316.3	382.1	0.9%
132 kV CB (ID & OD)	#	692.8	679.6	694.0	-1.9%
Overhead Lines - Reconductoring					
33kV Tower Line	km	39.1	39.0	-	-0.3%
66kV Tower Line	km	68.4	53.4	-	-21.9%
132 kV Pole Line	km	52.9	52.9	-	0.0%
132 kV Tower Line	km	65.0	82.1	-	26.3%
Support - Replacement					
33kV Tower	#	35.8	39.2	0.0	9.4%
66kV Tower	#	68.4	65.0	88.6	-5.0%
132 kV Pole	#	2.6	2.6	7.7	0.0%
132 kV Tower	#	108.9	108.9	108.9	0.0%
Refurbishment and Fittings					
132 kV Tower Refurbishment	#	5.0	N/A	0.0	N/A
132 kV Fittings	#	4.5	4.5	5.1	0.0%

B.2 LV Network Data

Table. Appendix-2 LV underground cable data

Size mm²	Application	New build size	Resistance Phase R W /km	Resistance Neutral R W /km	Reactance Phase jX W /km	Reactance Neutral jX W /km	Continuous Rating (Summer) Laid Direct AMPS	Continuous Rating (Summer) Ducted AMPS
4 mm²cu	Street Lighting		4.52	4.8	0.054		53	44
25 mm² Hybrid	Street Lighting	✓	1.180	1.240	0.043		115	94
35 mm²Hybrid	1 Ø service	✓	0.851	0.900	0.041		140	115
35 mm² HCN	3 Ø service	✓	0.939	0.939	0.076	0.015	132	106
35 mm² Wavecon	3 Ø service	✓	0.939	0.939	0.076	0.015	132	106
95 mm² Wavecon	Main/Service	✓	0.320	0.320	0.075	0.016	245	201
185 mm² Wavecon	Main/Service	✓	0.164	0.164	0.074	0.014	355	292
300 mm² Wavecon	Main/Service	✓	0.100	0.164	0.073	0.011	470	382
600 mm²XLPE single core	Transformer Tails	✓	0.0515	0.2	0.088	0.088	See Cables Cable Laying & Accessories Manual section 2.1.3	
35 mm² Alpex	3 Ø service		0.939	0.939	0.076	0.015	132	106
70 mm²Alpex	Main/Service		0.443	0.443	0.076	0.015	196	159
120 mm²Alpex	Main/Service		0.253	0.253	0.073	0.015	265	223
185 mm²Alpex	Main/Service		0.164	0.164	0.074	0.014	355	292
300 mm²Alpex	Main/Service		0.100	0.164	0.073	0.011	470	382
Consac – Paper Insulated Aluminium Sheathed						*based on Alpex*		
70 mm² Consac	Main/Service		0.433	0.433	0.061	*0.015*	185	150
95 mm² Consac	Main/Service		0.320	0.320	0.069	*0.015*	220	180
120 mm² Consac	Main/Service		0.253	0.253	0.069	*0.015*	250	210
150 mm² Consac	Main/Service		0.206	0.206	0.068	*0.015*	280	235
185 mm² Consac	Main/Service		0.165	0.165	0.068	*0.014*	320	265
240 mm² Consac	Main/Service		0.125	0.125	0.068	*0.014*	370	310
300 mm² Consac	Main/Service		0.100	0.100	0.068	*0.014*	420	350
PILC - Paper Insulated Lead Covered								
4/35 mm²al	Main/Service		0.868	0.868	0.075	0.075	125	105
4/95 mm²al	Main/Service		0.320	0.320	0.070	0.070	225	185
4/185 mm²al	Main/Service		0.164	0.164	0.068	0.068	330	275
4/300 mm²al	Main/Service		0.100	0.164	0.067	0.067	430	360
0.1 in² al	Main/Service		0.456	0.456	0.073	0.073	185	150
0.15 in² al	Main/Service		0.312	0.312	0.070	0.070	225	185
0.2 in² al	Main/Service		0.234	0.234	0.069	0.069	270	220
0.25 in² al	Main/Service		0.187	0.187	0.069	0.069	310	255
0.3 in² al	Main/Service		0.152	0.152	0.068	0.068	350	290
0.5 in² al	Main/Service		0.092	0.092	0.067	0.067	450	375
0.0225 in² cu	Main/Service		1.258	1.258	0.086	0.086	100	83
0.04 in² cu	Main/Service		0.703	0.703	0.079	0.079	140	115
0.06 in² cu	Main/Service		0.463	0.463	0.076	0.076	175	140
0.1 in² cu	Main/Service		0.276	0.276	0.073	0.073	240	195
0.15 in² cu	Main/Service		0.188	0.188	0.070	0.070	290	240
0.2 in² cu	Main/Service		0.142	0.142	0.069	0.069	345	285
0.25 in² cu	Main/Service		0.113	0.113	0.069	0.069	395	325
0.3 in² cu	Main/Service		0.092	0.092	0.068	0.068	445	385
0.4 in² cu	Main/Service		0.068	0.068	0.068	0.068	520	430

Resistance values are DC at 20°C	Maximum Conductor temperature:- - Wavecon & Alpex 90°C (XLPE) - Hybrid 70°C (PVC) - PILC and Consac 80°C	Depth of lay 0.45m Ground temperature 15 °C (Summer) Soil thermal resistivity 1.2 °C m/w (Summer)

B.3 IEEE Reliability Test System 1996

Table. Appendix-3 Weekly peak load in percent of annual peak

Week	Peak Load	Week	Peak Load
1	86.2	27	75.5
2	90	28	81.6
3	87.8	29	80.1
4	83.4	30	88
5	88	31	72.2
6	84.1	32	77.6
7	83.2	33	80
8	80.6	34	72.9
9	74	35	72.6
10	73.7	36	70.5
11	71.5	37	78
12	72.7	38	69.5
13	70.4	39	72.4
14	75	40	72.4
15	72.1	41	74.3
16	80	42	74.4
17	75.4	43	80
18	83.7	44	88.1
19	87	45	88.5
20	88	46	90.9
21	85.6	47	94
22	81.1	48	89
23	90	49	94.2
24	88.7	50	97
25	89.6	51	100
26	86.1	52	95.2

Table. Appendix-4 Daily load in percent of weekly peak

Day	Peak Load
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

Table. Appendix-5 Hourly peak load in percent of daily peak

Hour	Winter Weeks 1 -8 & 44 - 52		Summer Weeks 18 -30		Spring/Fall Weeks 9-17 & 31 - 43	
	Week day	Week end	Week day	Week end	Week day	Week end
12-1 A.M	67	78	64	74	63	75
1-2	63	72	60	70	62	73
2-3	60	68	58	66	60	69
3-4	59	66	56	65	58	66
4-5	59	64	56	64	59	65
5-6	60	65	58	62	65	65
6-7	74	66	64	62	72	68
7-8	86	70	76	66	85	74
8-9	95	80	87	81	95	83
9-10	96	88	95	86	99	89
10-11	96	90	99	91	100	92
11-Noon	95	91	100	93	99	94
Noon-1 P.M	95	90	99	93	93	91
1-2	95	88	100	92	92	90
2-3	93	87	100	91	90	90
3-4	94	87	97	91	88	86
4-5	99	91	96	92	90	85
5-6	100	100	96	94	92	88
6-7	100	99	93	95	96	92
7-8	96	97	92	95	98	100
8-9	91	94	92	100	96	97
9-10	83	92	93	93	90	95
10-11	73	87	87	88	80	90
11-12	63	81	72	80	70	85

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